Innovating with technology in team contexts: A trait activation theory perspective

Completed Research Paper

Massimo Magni
Bocconi University
Department of Management & Technology
Via Roentgen, 1
20136 Milano - Italy
Massimo.magni@unibocconi.it

Likoebe M. Maruping
Department of Computer Information Systems
College of Business
University of Louisville
Louisville, KY 40292 - U.S.A
likoebe.maruping@louisville.edu

Leonardo Caporarello
Bocconi University
Department of Management & Technology
Via Roentgen, 1
20136 Milano - Italy
Leonardo.caporarello@unibocconi.it

Stefano Basaglia
University of Bergamo
Via dei Caniana 2
24127 Bergamo - Italy
basaglia@unibg.it

Abstract

Noting the limited research on technology exploration in team contexts, we draw on trait activation theory to understand what drives users to experiment with new technology. We identify personal innovativeness in IT (PIIT) as an important situation-specific trait that influences individual-level efforts to try to innovate with technology. We also identify team learning behavior as an important team-level intervention that levels the playing field for trying to innovate with technology. We test our cross-level model in a one-year field study of 268 employees embedded in 48 organizational work teams. The results of our analysis show that (1) PIIT predicts trying to innovate with technology, (2) team learning behavior has a cross-level direct effect on trying to innovate with technology, and (3) team learning behavior has a cross-level moderating influence on the relationship between PIIT and trying to innovate with technology. We discuss the implications of our findings for research and practice.

Keywords: Technology exploration, multilevel research, user behavior, PIIT

Introduction

Investment in information technology (IT) still accounts for a significant proportion of overall spending in organizations and is projected to continue growing in the coming years (IDC 2010). A rich literature has emerged to understand how to get employees to use the systems in which organizations invest (Venkatesh et al. 2007; Sun and Zhang 2006). With the expansive shift toward team-based structures for organizing work, a majority of employees in organizations find themselves involved in some form of teamwork as a fundamental part of their jobs (Ilgen et al. 2005; Manz and Sims 2001). Recent estimates suggest that over 80% of Fortune 500 companies are utilizing team-based structures to organize work. Consequently, a strong emphasis has been placed on investment in collaborative technologies (e.g., , document sharing, video conferencing, and web conferencing) to support these new team-based work structures (Forrester 2007). Unfortunately, organizations face challenges related to the underutilization of technologies. Previous research has found that individuals underutilize newly introduced technologies, often limiting their interaction with a system to a narrow set of features (Rigby et al. 2002; Ross and Weill 2002). Indeed, Jasperson et al. (2005) note that employees "employ quite narrow feature breadths, operate at low levels of feature use, and rarely initiate technology- or task-related extensions of the available features" (p. 526). In a similar vein, Ahuja and Thatcher (2005) point out that it is "an everyday challenge for managers to find ways of facilitating IT-based innovation and creativity" (p. 428). Thus, as organizations seek to realize the benefits of these investments, there is significant interest in how employees can be motivated to innovate by exploring ways to integrate the features provided by these collaborative technologies into their work in an effort to enhance productivity.

Fostering innovation (or innovative behavior) among employees has been a perennial challenge for organizations (Amabile and Khaire 2008; Shalley et al. 2004). Motivating employees to innovate with newly implemented technologies has proven to be especially difficult for managers, prompting calls for future research to examine users' exploratory behaviors that are oriented toward innovation and identification of new ways of performing work activities, rather than the use of routine system features (Ahuja and Thatcher 2005; Gupta and Karahanna 2004; Jasperson et al. 2005). Such exploration behavior is widely expected to lead to value-added uses of technology in organizational settings (Ahuja and Thatcher 2005; Gupta and Karahanna 2004; Nambisan et al. 1999). In response to this exigency, recent literature has begun to identify factors that promote such behavior. For instance, Ahuja and Thatcher (2005) found that autonomous work structures can promote innovation with IT among employees. Li and Hsieh (2007) found perceived usefulness and intrinsic motivation to be predictors of intention to explore a newly implemented system. Magni et al. (2010) recently identified hedonic and instrumental factors that drive the intention to explore features in mobile devices. Taken together, this extant research suggests that individual and work environment factors play a role in promoting IT exploration behavior.

Although this prior research serves as an important stepping stone toward understanding how to facilitate exploration of IT among employees, several important theoretical gaps remain. First, prior work on exploration of IT—and, indeed, the broader IT adoption and use literature—has not incorporated the role of team-based structures into understanding what drives employees to innovate with IT. This is theoretically significant because collaborative technologies are deployed in team settings (Karahanna et al. 2002; Sarker and Valacich 2010) and, therefore, employees' behavior and reaction towards novel situations—such as a new technology introduction—is likely to be shaped by shared interpretations, experiences, and prescriptions among team members (Morgeson and Hofmann 1999; Orlikowski et al. 1995; Sarker and Valacich 2010). Further reinforcing this notion, Gallivan et al. (2005) note that individual decisions about technology use are largely influenced by proximal social others and highlight the need for research to incorporate "influences at levels beyond the individual user that shape how employees use IT in their jobs" (p. 155), suggesting that such influences could exist at the level of the workgroup. On empirical grounds, this gap in the literature is significant because the failure to account for team-level influences in examining individual technology exploration behavior can lead researchers to draw erroneous conclusions about relationships at the individual level of analysis—referred to as the contextual fallacy (Burton-Jones and Gallivan 2007; Rousseau 1985; Sarker and Valacich 2010). Second, because a large proportion of employees work in teams, it is important to understand how the team context influences innovation with IT among employees with different dispositions toward exploration. To date, research has yet to identify potential levers at the team-level that can facilitate such IT exploration behavior. In the context of team settings, interventions need to be targeted at the teams as a collective rather than at individual members. Identification of such factors can help managers in creating environmental conditions that are favorable for innovation with IT and can be applied to collectives (Ahuja and Thatcher 2005; Magni et al. 2010). These theoretical gaps have an inherently cross-level focus that requires explanation of the complex interplay between individual differences and team context. Efforts to bridge the micro-level (e.g., individual) and meso-level (e.g. team) divide remain limited in the IT adoption and use literature (Burton-Jones and Gallivan 2007).

The objective of this research is to address the theoretical gaps identified above by developing and testing a cross-level model of individual technology-related differences, team context, and innovation with IT in the workplace. Drawing on trait activation theory (Tett and Burnett 2003), we identify personal innovativeness toward IT (PIIT) as a situation-specific trait that promotes IT exploration behavior in the context of new technology implementation. We also identify team learning behavior as a team-level contextual variable that facilitates IT exploration behavior. Consistent with prior research, innovative behaviors toward IT refer to the search for new applications of a technology through the use of additional features or the use of basic features in a new way (Ahuja and Thatcher 2005; Gupta and Karahanna 2004; Nambisan et al. 1999). A secondary objective of this work is to move beyond an exclusive focus on individual-level factors in understanding post-adoptive use of technology and to instead incorporate factors at the meso-level (e.g., team level) so as to bridge the micro-meso divide (Rousseau 2010). Research on IT adoption and use remains lacking in this regard and there is a significant need for work that can shed light on the connections between meso-level factors and individual-level technology use outcomes (Burton-Jones and Gallivan 2007). The research model is illustrated in Figure 1 below.

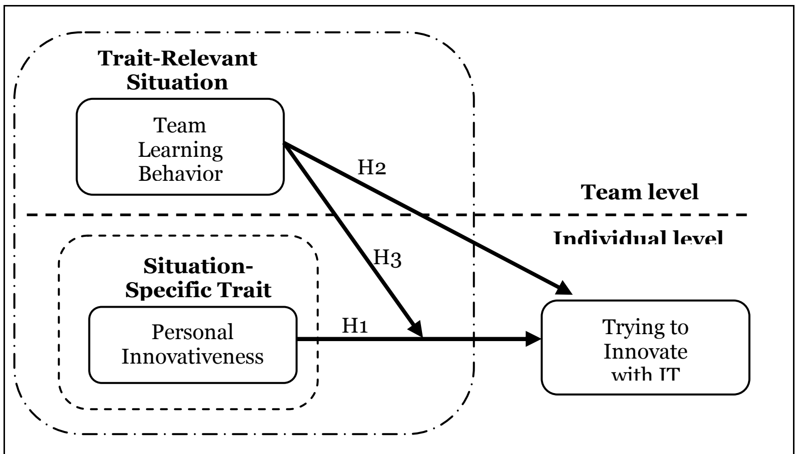

Figure 1. Research Model

Theory and Hypotheses

Trait Activation Theory

It has long been recognized that individual traits—predispositions of individuals to behave in consistent ways in response to situational stimuli—are an important determinant of how employees behave in the work environment (Day and Silverman 1989; Tett and Guterman 2000). *Trait activation theory* explains how the magnitude and direction of the relationship between individual traits and behavior vary as a function of the trait-relevance of the situation (Tett and Burnett 2003). The theory recognizes that (1) behavioral consistencies represented by traits allow prediction of future behavior based on past behavior, (2) interpersonal differences in behavioral tendencies underscore the need for trait descriptions, and (3) traits are latent propensities that reside within individuals and are triggered by situational stimuli (Tett and Burnett 2003). Consistent with the principles underlying person-situation interactionism, a major tenet of trait activation theory is that traits are expressed as reactions to trait-specific situational cues (Tett and Guterman 2000). This is also in keeping with the broader literature on situation-specific traits that describe behavioral consistencies in how individuals respond to specific, clearly identifiable situations (Day and Silverman 1989; Thatcher and Perrewe 2002). Thus, in order for a trait to be activated, the situation must be trait-relevant so as to reveal an individual's standing on the trait (Tett and Guterman 2000). A situation is trait-relevant when "it is thematically connected by the provision of cues" (Tett and Burnett 2003, p. 502). The implementation of new technologies in organizations represents a situation which has been shown to evoke situation-specific traits among users (Magni et al. 2010; Thatcher and Perrewe 2002).

Personnal Innovativeness in IT (PIIT) and Trying to Innovate

Prior research in the technology use domain has found specific traits to be particularly valuable in predicting individuals' behavior in the context of technology implementations. Situation-specific traits are relatively stable descriptors that "predispose individuals to respond to stimuli in a consistent manner within a narrowly defined context or group of target objects" (Thatcher and Perrewe 2002, p. 383). Although several individual traits could potentially affect how individuals respond to new technology (e.g. Thatcher and Perrewe 2002), personal innovativeness has been recognized to play a pivotal role in understanding individual behavior toward technological innovations (Agarwal 2000; Agarwal and Prasad 1998; Thatcher and Perrewe 2002). In recognition of this pivotal role, Agarwal and Prasad (1998) developed the concept of *personal innovativeness in the domain of IT* (PIIT), a situation-specific trait reflecting individuals' willingness to try out any new technology within a particular context. Thatcher and Perrewe (2002) conceptualize PIIT as a stable situation-specific trait in that it is expected to have a consistent role in explaining user behavior across situations involving technology. PIIT fosters an intrinsic interest in trying out the technology itself and exploring its features (Yi et al. 2006). This interest in the technology is intrinsically motivated and it leads to a deeper and more intensive engagement with the technology—resulting in individual willingness to perform exploratory behaviors (Magni et al. 2010). Hence, we focus on PIIT as an important situation-specific trait that predicts employees' efforts to innovate with technology.

Trying to innovate with IT represents a post-adoption goal directed behavior in which a user attempts to identify novel uses of workplace technology to enhance performance (Ahuja and Thatcher 2005). The concept is rooted in Bagozzi and Warshaw's (1990) theory of trying, which notes that goal-directed behaviors require individuals to engage in attempts—trying (with volitional, motivational, and cognitive undertones)—that help convert intentions into actual behavior. This is especially true where environmental conditions can impede the predictive validity of intentions in explaining IT-related behavior (Ahuja and Thatcher 2005; Bagozzi and Warshaw 1990; Venkatesh et al. 2006; Venkatesh et al. 2008). In the context of trying to innovate with IT, trying engenders experimental attempts to identify novel, productive, uses of IT to enhance work effectiveness (Ahuja and Thatcher 2005). Ahuja and Thatcher (2005) argue that trying to innovate with IT represents a more robust way of understanding how employees relate to IT at a post-adoptive stage.

Drawing on trait activation theory, we expect that PIIT will be positively related to trying to innovate with IT. New technology implementation creates situational uncertainty (Griffith 1999; Spender and Kessler 1995). Griffith (1999) notes that when encountered, technologies—as constellations of features—trigger individuals to engage in sensemaking as a precursor to adaptation and sustained usage. This sensemaking is triggered due to uncertainty and/or ambiguity about the features themselves as well as an understanding of how those features might be used in one's work (Griffith 1999; Louis and Sutton 1991). Incorporating the use of various technology features into an employee's work constitutes a marked departure from the rhythm and routines they already have in place for completing their tasks. As such, employees faced with the prospect of employing a new technology in their work are considered to be facing some situational novelty. Such technology-induced situational novelty constitutes a trait-relevent cue that should evoke employees' predisposition toward exploration of new technology as part of the sensemaking process (Tett and Burnett 2003; Thatcher and Perrewe 2002). In other words, the situational novelty created by new technology implementation should trigger the situation-specific trait of PIIT, which will differentiate innovative from non-innovative individuals in responding to the situation.

Previous research notes that innovative individuals are more likely to actively seek information in dealing with novel situations (Rogers 1995). In the context of new technology implementation, innovative individuals—i.e., those with high PIIT—are more likely to search for the new possibilities offered by the technology (Agarwal and Prasad 1998). Such reasoning is consistent with previous research which suggests that the propensity to innovate is tied to individuals' willingness to change and to challenge the traditional way they perform their tasks (Thatcher and Perrewe 2002). Indeed, individuals with a stronger PIIT are expected to be more intrinsically motivated to seek out novel ways to deal with the technology; efforts that by definition involve uncertain and untried approaches that possess a high likelihood of error or potential failure (Magni et al. 2010). In contrast, individuals with lower PIIT are expected to show a weaker desire to search for novelty and a greater preference for maintaining the status quo (Oreg 2003) and to perform routinized behaviors that are not compatible with the new situation (Tichy 1983). Magni et al. (2010) found that users with high PIIT were more inclined to form an intention to explore novel applications of new technology compared to users with low PIIT. Thus, we hypothesize that PIIT positively influences trying to innovate with IT.

H1: *PIIT will be positively associated with trying to innovate with IT.*

Cross-level Effects of Team Learning Behavior

Given the heightened task and outcome interdependence in organizational work teams (Wageman 1995), the behavioral responses of employees to new technology are likely to exhibit some homogeneity within teams and heterogeneity across teams (Burton-Jones and Gallivan 2007; Gallivan et al. 2005). Teams have been conceptualized as social entities that develop shared attitudes and behavioral patterns through social interaction as well as through the exposure of team members to the same procedures, policies and experiences (Anderson and West 1998; Wilkens and London 2006). Employees' reactions to technology have been shown to be prone to influence by proximal social others (Gallivan et al. 2005; George et al. 1995). In a team-based setting, teammates are the most proximal source of influence on one's work-related decision making (Gallivan et al. 2005). Therefore, individual team members' attempts at trying to innovate with IT are likely to be shaped by attitudes and practices at the team-level. Such top-down (contextual) effects are argued to be particularly strong in tight-knit contexts such as teams (Kozlowski and Klein 2000; Mathieu and Taylor 2007). In accordance with the multilevel principle of bond strength (Kozlowski and Klein 2000), we expect this to be especially true for team-level practices that tap into the behavior of interest—trying to innovate.[1]

Team learning behavior refers to the extent to which a team engages in activities and reflection that are aimed at enhancing innovative knowledge (Edmondson 2002). Action refers to the existence of team practices that promote experimentation, innovation, and risk taking (Edmondson 1999). Reflection represents an environment in which team members favor inquiry and dialogue, and encourage collaboration (Garvin 1993). Viewed from this perspective, team learning is a process rather than an outcome and therefore has the potential to influence the behavior of individual team members (Edmondson 1999; Hirst et al. 2009). In particular, team learning behavior has been viewed as an instrumental contextual element in fostering a desire by individual team members to learn and experiment. This is achieved by reducing the potential for psychological risks associated with failure, which under less favorable circumstances can be met with social reprimand from one's interdependent coworkers (Edmondson 1999; Hirst et al. 2009). Through such a context, greater amounts of information are made available to team members and those who might otherwise refrain from learning and experimentation are emboldened to engage in such activity. Among users of a new technology, team members actively seek and discuss novel applications of the technology through experimentation. Further, lessons learned from trying unconventional approaches to using a feature are made available to all team members (Nambisan et al. 1999). This collectively advocated engagement in the discovery process minimizes the psychological risks associated with activities that may yield multiple failures before a value-adding use of technology is identified (Nambisan et al. 1999). This is significant since the interdependent work of team members may make them reluctant to engage in experimental behavior that

---

[1]The principle of bond strength states that in multilevel contexts, antecedents within a level of analysis, or at a more proximal level of analysis, exert a more powerful influence on outcomes of interest than hierarchically distal antecedents (Kozlowski and Klein 2000). For example, antecedents at the team-level of analysis might be expected to exert a stronger influence on individual-level outcomes compared to antecedents at the organizational level of analysis. This principle also suggests that domain-relevant antecedents at proximal levels of analysis should exert more of an influence than non-domain relevant antecedents (Mathieu and Taylor 2007).

impacts their teammates' ability to do their work. When the team as a whole provides a supportive structure, team members who would otherwise avoid such experimental and learning activities are able to benefit. Thus, on average, team members who find themselves embedded in teams that exhibit learning behaviors are more likely to engage in trying to innovate. In contrast, in team contexts that exhibit low team learning behavior, team members are likely to avoid engaging in innovative behaviors with the technology due to a lack of social support and for fear of reprimand by teammates. As such, we expect team learning behavior to be positively associated with trying to innovate with IT among team members.

H2: *Team learning behavior will have a positive cross-level association with trying to innovate with IT.*

Trait Activation in Context: PIIT and Team Learning Behavior

For individual team members dealing with new technology implementation, team learning behavior represents a trait-relevant contextual element that can trigger one's predisposition to engage in innovative behavior over and above the cues represented by the new technology itself. In a team context characterized by low team learning behavior, the social support that encourages trying to innovate is absent. Consequently, due to the situation-specific trait activation induced by the new technology, PIIT should be a key differentiator between whether or not a team member tries to innovate with the technology (Magni et al. 2010; Thatcher and Perrewe 2002). That is, barring social support for the activity, only those team members with the innate predisposition to explore and experiment with the technology—as represented by those with higher PIIT—will actually try to innovate. In contrast, individuals with low levels of PIIT do not possess an innate propensity to try out new technology (i.e., there is no trait to be activated) and therefore are unlikely to try to innovate given the lack of social support for such activity. At higher levels of PIIT, the incremental influence of predisposition to explore on trying to innovate is likely to decrease. A couple of reasons underlie this diminishing impact. First, as a goal-directed behavior, trying to innovate has an inherently instrumental motivation—to identify value-added applications for technology (Ahuja and Thatcher 2005). As such, attempts to innovate are not driven solely by the intrinsic motivation for the activity itself, but by the potential for high returns in work effectiveness (Nambisan et al. 1999). Similar observations have been made in the context of learning where diminishing returns to learning occur at high levels (e.g., Bunderson and Sutcliffe2003; He and Wong 2004). Those who strike a balance between learning and application are able to achieve greater returns to their learning efforts (Hirst et al. 2009). Consistent with this notion, we expect that those with high levels of PIIT are no more likely to engage in trying to innovate with technology than those at moderate levels of PIIT since the interests in exploring the technology must be balanced against the performance-enhancing applications of discoveries. Exploration for the sake of exploration—which is likely to occur among those with high PIIT—must be tempered in a work context that demands results (Agarwal 2000; Nambisan et al. 1999). Second, in a context of low team learning behavior, where experimentation is not actively supported, zealots who possess very high levels of PIIT are likely to face social reprimand from their task and outcome interdependent teammates. To the extent that teammates do not assign an equal amount of value to exploratory behaviors, they are like to express concern when the excessive pursuit of such activities affects the team as a whole. On the whole, this suggests an inverted curvi-linear relationship between PIIT and trying to innovate in teams with low learning behavior.

In contrast to the team contexts in which team learning behavior is low, team contexts where team learning behavior is high are expected to weaken the relationship between PIIT and trying to innovate. In line with trait activation theory, high team learning behavior constitutes a trait-relevant context for exploration and experimentation (Hirst et al. 2009). The information-seeking, experimentation, and reflection activities embodied in team learning behavior are consistent with the disposition embodied in individuals with high PIIT. As a result, high team learning behavior contexts activate the situation-specific trait of PIIT, influencing members to try to innovate (Tett and Burnett 2003). Given the social/environmental support for such behavior, PIIT should have a linear positive relationship with trying to innovate. From a team context perspective, the activation of PIIT can be traced back to the fact that teamwork requires coordination and cooperation among team members and the process of experimentation with new technology can be personally risky for individuals as they engage in a trial-and-error process of identifying solutions that work (Orlikowski 1993; Thomke 1998; Vera and Crossan 2005). While PIIT reflects an individual propensity to be more experimental with IT, a common fear among users is that their experimental actions will precipitate negative reactions from their interdependent teammates

(Edmondson 1999). It is therefore essential for there to be norms that emphasize the value of such behavior so that the individual trait of PIIT can be activated in an environmental context where efforts to innovate with the technology can be pursued without fear of reprisal. Team learning behavior fosters such relationship because it creates an environment in which experimentation and individual initiative taking is supported (Edmondson 1999). Moreover, team learning behavior, through reducing the psychological risks associated with exploration-oriented behavior, favors the expression of PIIT because it signals that errors in the exploration process are less likely to elicit negative feedback and that the team encourages people to try to innovate. Finally, as argued in H2, high team learning behavior encourages exploration and experimentation with the technology among those who might otherwise not be inclined to engage in such behavior. To the extent that team learning behavior constitutes norms for team members to follow, the high team learning context can be characterized as being a strong situation. Tett and Burnett (2003) note that in strong situations, even though trait activation may occur, the strength of the context results in all individuals exhibiting the same behavior, regardless of their predispositions. This logic suggests that on average in team contexts with high team learning behavior, more members are likely to try to innovate with technology, regardless of their predisposition to do so. Thus, in teams characterized by high team learning behavior, PIIT should be a weaker predictor of trying to innovate.

H3: *Team learning behavior will have a cross-level moderation effect on the relationship between individual PIIT and trying to innovate. When team learning behavior is low, PIIT will have a positive curvi-linear relationship with trying to innovate; when team learning behavior is high, PIIT will have a positive linear relationship with trying to innovate.*

Method

Sample and Participants

To test our research model we conducted field studies in two large European firms. One of the participating firms was based in the retail industry while the other was based in the banking industry. The participating firms were the sites for recent new collaborative technology introductions. Specifically, both firms had recently implemented a new collaborative-technology system to support all technology-mediated communications among employees for such activities as agenda sharing, information sharing, mobility management, and event coordination. Use of the system was strongly encouraged by upper management. However, there was no policy in place for non-compliance, underscoring that system use was voluntary. The participating firms each employed a team-based structure for organizing work. Consistent with the definition of work teams, all teams had a clearly defined membership (i.e. each member belonged to just one team), operated within organizational boundaries, and worked on multiple measurable tasks (Hackman 1987). Across the two firms, a total of 810 employees comprising 129 teams were targeted for participation in the study. Two waves of data collection were conducted about one year apart. Out of the 810 employees, 410 usable surveys from members of 69 teams were completed in the first wave, yielding individual-level and team-level response rates of 50.6% and 53.4% respectively. Of the total number of participants in the study, 183 (45%) were women. The average age of participants was 41.12 (SD = 9.16). A majority (63%) of the participants had been with their respective firms for over 10 years and fewer than 9% had worked for their firms for less than 3 years. In the second wave of data collection, we targeted employees who had responded to the first survey. Out of the 410 respondents from the first survey, a total of 268 employees in 48 teams responded. We compared employees who participated in both waves of data collection with employees who only participated in the first wave and found no significant differences in demographics (e.g., age, gender, organizational tenure) usage (e.g., duration, frequency, scope). Our analyses and hypothesis tests are based on employees who responded to both surveys. Because high response rate within the teams are required to support the use of the data at the team level of analysis (Barrick et al. 2007), the 48 teams included in the final analysis had 70 percent of their members responding to the survey.

Measurement

We operationalized the constructs in the model using existing scales. Where relevant, we report on the within-group agreement index ($r_{wg(j)}$), and intra class correlation coefficients (ICC) in justifying aggregation of individual-level scores to the team level. The $r_{wg(j)}$ indicates the extent to which group members' responses to the survey converge greater than would be expected by chance (James et al. 1984).

The ICC(1) reflects between-group variance in individual responses and the ICC(2) indicates the stability of the group-level means (Bliese 2000).

Trying to innovate. We used a seven-item scale based on Ahuja and Thatcher's (2005) trying to innovate scale. The scale measures the extent to which employees explored novel ways to use the system in their work. The scale had a reliability of .88.

Personal innovativeness in IT (PIIT). A four-item scale developed by Agarwal and Prasad (1998) was used to measure PIIT. The reliability for the scale was .75.

Team learning behavior. We measured team learning behavior using a five-item scale adapted from Edmondson (1999). We modified the items to reflect the teams' learning behavior toward newly implemented technology. Sample items include" we help each other to incorporate the [*name of system*] into our daily work activities" and "we support each other's efforts to integrate the [*name of system*] into our work". The reliability for this scale was .82. As noted earlier, because team learning behavior is a team-level construct, it was necessary to determine whether aggregation of the individual-level scores on this scale to the team level was appropriate. The median $r_{wg(j)}$ for team learning behavior was .91, well above the recommended threshold of .70 (James et al. 1984). Results of a one-way ANOVA indicated significant differences across teams in reported levels of team learning behavior ($F_{47, 265} = 2.11$, $p < .001$). The ICC(1) and ICC(2) values for this scale are .18 and .53 respectively. Taken together, this information suggests that it is appropriate to aggregate the individual scores. Thus, we averaged the individual team learning behavior scores within each team to compute a single team-level score.

Control variables. We included several important control variables that are relevant to post-adoptive use of technology. At the individual level, we drew on Davis (1989) to measure employees' perceived usefulness of the system, as this has consistently been found to influence post-adoptive technology use (e.g., Karahanna et al. 1999; Venkatesh et al. 2003) and technology exploration behavior (e.g., Magni et al. 2010). The reliability of the scale was .78. We also controlled for age and gender, as these have been shown to explain variation in the use of technology (see Ahuja and Thatcher 2005; Gefen and Straub 1997; Morris and Venkatesh 2000; Venkatesh et al. 2003; and Venkatesh and Morris 2000 for examples). Organizational tenure was also included as a control variable as employees who were new to the organization may feel pressure to use the system in order to fit in. Finally, we measured usage scope as the number of system features employees used in their work. We provided a table listing all ten of the features available in the system. Respondents were asked to indicate whether or not they used each of the system features listed. The usage scope score is the sum of features used by a respondent. At the team-level, we controlled for team size as larger teams were more likely to require the exploration of features to coordinate interdependent work across more individuals. We also controlled for team tenure. Finally, we controlled for the dispersion of team members since individuals in teams that were more distributed would be more likely to explore the system to coordinate work across sites. We measured team distributedness using O'Leary and Cummings (2007) site index measure. In the context of the current study, we measured the number of different buildings in which a team's members were located.

Procedure

As noted earlier, the data for this study were collected in two waves. Prior to data collection, we worked closely with management in the participating firms. We conducted interviews with each firm's IT managers to gain an understanding of the work context and the circumstances surrounding the implementation of the new system. The first survey was administered to participants about 1.5 months post-implementation and was designed to measure the demographic information of participants, perceived usefulness, baseline feature usage scope, as well as PIIT. At time 2 (12 months after the first wave of data collection), we administered the second questionnaire to measure participants' exploration behavior through the trying to innovate with IT scale. We also asked employees to respond to questions about their team's learning behavior with respect to the new system.

Analysis and Results

To assess the measurement model, we conducted a confirmatory factor analysis (CFA). We focused on the comparative fit index (CFI) and standardized root-mean-square residual (SRMR) as indicators of model fit (Bentler 1990; Hu and Bentler 1999). The CFI is generally accepted as the best estimate of the population value for a model (Medesker et al. 1994). Values ≥ .95 are generally considered to represent good fit (Hu and Bentler 1999). The SRMR reflects the average standardized residual per degree of freedom. Values ≤ .08 are considered to represent relatively good fit for the model (Hu and Bentler 1999). Our 3-factor solution involving trying to innovate, team learning behavior and personal innovativeness with IT indicated that the measurement model had reasonably good fit to the data (CFI = .96, SRMR = .06, χ^2 = 357.20, $p < .001$). We also assessed the fit of a common method model by adding a common method factor in which all indicators were specified to have dual loadings (on the common method factor and the corresponding latent factor). Following Podsakoff et al. (2003), we constrained the correlations between the method factor and other latent constructs to 0. The fit of the common method model to the data was not significantly different from the measurement model (CFI = .97, SRMR = .04, χ^2 = 330.00, $p < .001$), suggesting that the addition of the common method factor did not significantly improve the model fit. Thus, concerns about common method bias are somewhat alleviated (Podsakoff et al. 2003). Convergent validity of the constructs was determined by examining the lambda values for the indicators and the average variance extracted (AVE). Results from the CFA indicate that all lambda values were above the recommended threshold of .50 (Hair et al. 1998). In addition, all AVEs were greater than .50, providing support for convergent validity. To determine whether discriminant validity is supported, we examined the square root of the AVE as well as the inter-construct correlations (Fornell and Larcker 1981). None of the inter-construct correlations was larger than the square root of the AVE, thus, providing support for discriminant validity.

Table 1. Descriptive Statistics and Inter-construct Correlations.

Variables	M	SD	1	2	3	4	5	6	7	8	9	10
Trying to innovate	3.22	0.80										
PIIT	3.03	0.59	.24**									
Team learning behavior	3.22	0.41	.17**	.16**								
Usage scope	4.53	1.75	.17**	.02	-.05							
Perceived usefulness	2.78	0.86	.13*	-.01	.04	.25**						
Organizational tenure	7.89	0.93	-.04	-.13*	-.05	-.12†	-.13*					
Age	42.56	9.02	-.08	-.16**	-.12†	-.07	-.05	.60**				
Gender	-	-	.01	.12*	-.04	-.07	.02	.06	-.04			
Team size	8.88	5.20	.04	.12†	-.09	.03	-.02	.01	.12†	-.01		
Team tenure	4.98	1.34	.04	.09	-.24**	-.07	.00	.03	.02	.02	-.09	
Team dispersion	2.82	1.74	.05	-.04	-.09	.07	-.03	.07	.16**	.08	.51**	.06

Notes: Level-1 (individual level) n = 268; level-2 (team level) n = 48.

1. *† p < .10, * p < .05, ** p < .01*
2. *Gender (0 = women, 1 = men).*

The correlations and descriptive statistics are shown in Table 1. As the table illustrates, trying to innovate with IT is positively correlated with PIIT ($r = .24$, $p < .001$) and team learning behavior ($r = .17$, $p < .01$). Given the hierarchically nested structure of the data and the cross-level nature of the research model, it was necessary to use a random coefficient modeling (RCM) technique for the analysis. RCM enables researchers to model and examine relationships that span levels of analysis and can meaningfully partition the variance components in outcome variables (Hofmann 1997; Raudenbush and Bryk 2002). In addition, RCM helps to reduce the potential for Type I and II errors that might arise if non-independence of observations is not accounted for (Bliese and Hanges 2004). In the context of the present study, the use of RCM was necessary for two reasons. First, individual employees were hierarchically nested within work teams. Second, our research model required us to test cross-level main and interaction effects pertaining to team learning behavior. We used hierarchical linear modeling (HLM) to test the research model (Raudenbush and Bryk 2002).

Table 2. Results of Random Coefficient Model Predicting Trying to Innovate with IT.

DV: Trying to Innovate with IT$_{(t2)}$	**Model 1**	**Model 2**
Controls (level-1):		
1. Organizational tenure$_{(t1)}$	-.02	-.01
2. Age$_{(t1)}$	-.01	-.01
3. Gender$_{(t1)}$	-.04	-.03
4. Perceived usefulness$_{(t1)}$	.13*	.14*
5. Usage scope$_{(t1)}$	.05†	.05†
6. Organization	-.11	-.11
Controls (level-2):		
7. Team size$_{(t1)}$	.02*	.01†
8. Team tenure$_{(t1)}$	.03	.01
9. Team dispersion$_{(t1)}$	.01	.00
Main effects (level-1):		
10. PIIT$_{(t1)}$ **(H1)**	.17**	14.**
Main effects (level-2):		
11. Team learning behavior$_{(t2)}$ **(H2)**	.17**	.02
Quadratic effects:		
12. PIIT-squared		.00
Cross-level interaction effects:		
13. PIIT x team learning behavior		.02
14. PIIT-squared x team learning behavior **(H3)**		.10**
R^2	.29**	.49**

Notes: Level-1 (individual level) n = 268; level-2 (team level) n = 48.
1. † *p < .10, * p < .05, ** p < .01, *** p < .001.*
2. *Gender (0 = women, 1 = men).*

The results of the models predicting trying to innovate are presented in Table 2. Although the deviance statistic is the best indicator of model fit in RCM (Raudenbush and Bryk 2002), it is also possible to compute a Pseudo-R^2 that is computed as a ratio of total variance from an unconditional model and unexplained variance from a conditional model (Snijders and Bosker 1999). However, caution is urged regarding interpretation of the Pseudo-R^2 as it can be unstable and has the potential to under- or over-estimate true effect sizes (Snijders and Bosker 1999). An alternative approach is to use the cross-level operator analysis to model the total variance (James and Williams 2000). The variance explained statistic produced by this approach is similar to a traditional R^2 from regression analysis. This approach yields a better estimate of the variance explained by the predictive model. We report this total R^2 in our results. As the results in Table 2 indicate, the main effects model (model 1) explains 29 percent of the variance in trying to innovate. Consistent with H1, we find that PIIT has a positive and significant influence on trying to innovate ($\beta = .17$, $p < .01$). Thus, H1 is supported. H2 predicted that team learning behavior would have a cross-level main effect on trying to innovate. The coefficient for team learning behavior is positive and significant ($\gamma = .17$, $p < .01$), suggesting that individuals in teams that have higher levels of learning behavior are more likely to try to innovate with the system compared to individuals in teams with lower levels of team learning behavior. This provides support for H2.

In the cross-level interaction model (model 2) we entered the linear and non-linear interaction terms (note that it is necessary to simultaneously include lower order interaction effects when testing non-linear interactions). The model explains 49 percent of the variance in trying to innovate ($\Delta R^2 = .20$, $p < .01$). H3 predicted that PIIT would have a curvi-linear relationship with trying to innovate, contingent on the level of team learning behavior. The interaction between team learning behavior and PIIT-squared is significant ($\gamma = .10$, $p < .01$). Following the guidelines of Aiken and West (1991), we plotted the relationship between PIIT and trying to innovate at one standard deviation above and below the mean for team learning behavior.

As the interaction plot in Figure 2 illustrates, in the context of low team learning behavior (one standard deviation below the mean), PIIT has a curvi-linear relationship with trying to innovate. A test of simple slopes (Aiken and West 1991) showed this curvi-linear effect to be significant ($b = -.18$, $p < .01$). At low to intermediate levels of PIIT the relationship between PIIT and trying to innovate is strongest, while at higher levels of PIIT the relationship becomes weaker. In contrast, in the context of high team learning behavior (one standard deviation above the mean) we find that PIIT does not have a curvi-linear relationship with trying to innovate ($b = .04$, $p = ns$). Instead the relationship is weakly positive and linear ($b = .18$, $p < .10$). This pattern is consistent with our prediction in H3. Hence, H3 receives support.

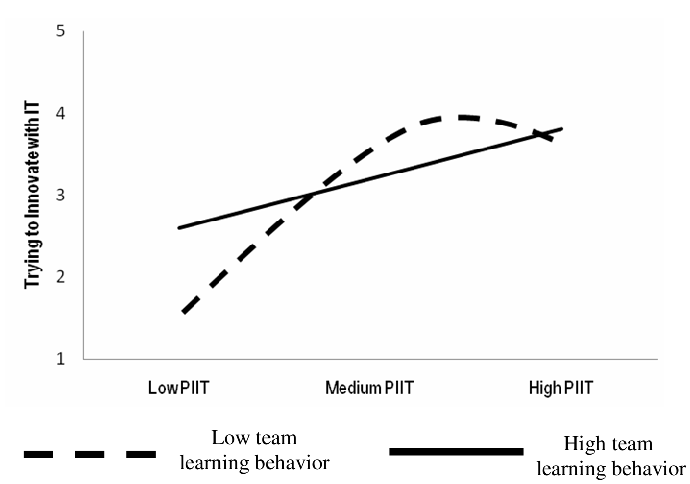

Figure 2. Cross-level Interaction between Team Learning Behavior and PIIT.

Discussion

The objective of this research was to understand the interplay between team context and individual innovative tendencies in influencing efforts to innovate with IT in the workplace. To this end, we adopted a cross-level approach and drew on trait activation-theory to explain how team context and individual situation-specific traits affect innovation with IT. We tested our cross-level longitudinal model in a sample of 268 employees nested in 48 work teams. We found that individual PIIT influences trying to innovate with IT and that team learning behavior has a cross-level direct influence on trying to innovate with IT. Moreover, consistent with interactional-dynamism, we found that team learning behavior moderates the relationship between PIIT and trying to innovate with IT. These findings corroborate our conceptual model by showing that the relationship between individuals' PIIT and trying to innovate is contingent on team learning behavior.

Theoretical Contributions and Implications for Research

Our model and results contribute to the IS literature in several important ways. First, the main contribution of our study lies in the adoption of a cross-level perspective to bridge micro-level (individual-level) and meso-level (team-level) drivers of innovation with IT. This approach advances the literature by modeling the complexity associated with technology implementation in organizations with team-based structures. While prior research on innovation with IT has tended to focus on employees working independently (e.g., Ahuja and Thatcher 2005; Magni et al. 2010), we augment the IS literature by recognizing and incorporating the social complexity that exists when employees are organized into teams that work interdependently. Burton-Jones and Gallivan (2007) underscored the value of examining such social complexity in the context of technology use and called for future research to incorporate factors at different levels of analysis. At the individual level of analysis, we drew on trait activation theory to identify PIIT as an important situation-specific trait that explains employees' effort to try to innovate with IT. Previous literature has not examined the role of individual differences in motivating such technology exploration behavior. In fact, Ahuja and Thatcher (2005)—who focused on overload and gender—call for future research to identify and examine individual differences that further explain trying to innovate with IT and they highlight personal innovativeness as a potential key determinant. Thus, this research contributes by identifying and examining the relationship between a key individual difference variable and trying to innovate with IT. This relationship is examined while giving consideration to the team context in which the employee is embedded.

Second, this research contributes to the IS literature by taking into account the role of team contextual factors in shaping individual efforts to try to innovate with IT. Although prior research has hinted at the importance of social contextual factors in shaping employees' reactions to technologies in the workplace (e.g., Gallivan et al. 2005; George et al. 1995), limited studies explicitly took this cross-level framework into account in studying how individual innovation with IT can be fostered. In this research, we not only modeled the cross-level structure in which employees were embedded—by taking team membership into account—we also identified team contextual factors—specifically team learning behavior—that influence individual team members' efforts to try to innovate with IT. Adopting a multilevel perspective allowed us to depart from the traditional conceptualization of contextual factors from an individual level of analysis (i.e. individual-level perceptions about the characteristics of the environment). We followed the suggestions outlined in previous multilevel research (Klein et al.1994; Kozlowski and Klein 2000; Morgeson and Hofmann 1999; Rousseau 1985) which posits that scholars who want to study how contextual variables affect individual outcomes need to be explicit about the level at which a specific concept is manifest within their theoretical model and the corresponding level at which the construct is represented. Following this perspective, we incorporated the role of team learning behavior. In so doing, we uncover a key intervention that fosters innovative behavior within teams. Our findings show that on average, individuals who are embedded within teams that exhibit learning behavior are more likely to try to innovate with IT, compared to individuals who are embedded in team contexts that do not exhibit these learning behaviors. This represents a critical attempt to bridge the gap between meso- and micro-approaches in technology use research (Burton-Jones and Gallivan 2007).

Third, based on trait-activation theory, our findings show an interesting cross-level interaction effect between team learning behavior and PIIT in shaping individual trying to innovate with IT. Specifically, we find that in team contexts characterized by low team learning behavior, the relationship between PIIT and trying to innovate has a curvilinear inverted U-shape—with the relationship being strongest at low to moderately high levels of PIIT and weaker at high levels of PIIT. In contrast, we find that in team contexts characterized by high team learning behavior, PIIT has a weak positive relationship with trying to innovate with IT. This result is striking in a couple of regards and it provides new insights into IT adoption research. First, it shows that the effect of PIIT varies across team contexts—that is, the effect of PIIT on trying to innovate depends on the team context in which the individual is embedded. Previous research has not taken such contextual influences into account. By taking team context into consideration, this result underscores the threat of the contextual fallacy—the fallacious assumption that the relationship between two constructs is consistent across situations (Rousseau 1985). Second, this result shows that team learning behavior levels the playing field with respect to trying to innovate with IT, such that even those who are not naturally inclined to experiment with new technology are willing to engage in exploratory and experimental interactions with IT, given the right environmental conditions. Consistent with trait activation theory, we find that teams with high learning behavior constitute a "strong" context which negates the role of individual traits in differentiating those with a natural inclination to experiment with technology and those who do not (Tett and Burnett 2003). Third, the curvilinear relationship between PIIT and trying to innovate in the context of low team learning behavior suggests that there are limits to the benefits of individual personal innovativeness when the context is not conductive for initiative and interpersonal risk-taking. The finding that the effects of PIIT on trying to innovate with IT diminish at a certain point is consistent with the notion that experimental behaviors need an environment in which individuals perceive a high level of psychological safety, in which they can engage in initiative taking without the fear of reprimand (Edmondson 1999). In sum, by focusing on a team-based setting, we demonstrate that team context plays a pivotal role in moderating the expression of individual situation-specific traits that drive innovation-oriented behavior (Taggar 2002).

Finally, our study contributes to the emerging literature on the organizational challenges to fostering individual innovative behaviors with IT which may lead to additional value-added uses of technology in the workplace. While prior research on individual interaction with technology has mainly focused on patterns of use—i.e., frequency, duration, or breadth of use (Venkatesh et al. 2003), considerably less research has gone beyond considerations of use to focus on more innovation-oriented behaviors. Thus, our results contribute to extant literature by advancing efforts to study factors which affect individual innovative behaviors toward technology. Advancing the literature on technology adoption in such a vein is particularly critical because it enhances our understanding of antecedents which favor successful innovation with technology. Consistent with the arguments posed by Ahuja and Thatcher (2005) our results complement previous research by uncovering those factors which allow individuals to identify successful applications of IT that optimize task performance and organizational processes.

Collectively this set of findings points to the importance of giving consideration to team-level context when studying individual innovative behaviors with technology. Through collectively embraced norms and practices, teams can serve as an effective mechanism for channeling employees' motivation and behavior towards new technologies in the workplace. Previous research has shown that managers play a vital role in shaping such collectively held norms of behavior and that these norms can sustain desirable behaviors across a variety of situations and encounters (e.g., Chen et al. 2007; Zhang and Bartol 2010). Additionally, the findings suggest that the impact of such collectively embraced norms on individual decisions about technology is not uniform across employees. Rather, the natural disposition of individuals plays a significant role in shaping the efficacy of such team-level interventions. Ultimately, the results of this research highlight the value and importance of considering factors at multiple levels of analysis in understanding the motivations underlying employees' attempt to innovate with technology in the workplace.

Strengths and Limitations

Our research study has several strengths that should be noted. First, our study design involved data collection from multiple sources within participating teams. In particular, we were able to get responses to questionnaire items from a majority of members in each team at two different points in time. This is particularly noteworthy given the difficulty of obtaining such data in a field setting. Second, our treatment of team learning behavior does not rely on a single source but reflects the shared perception of team members, offering a more accurate representation of the team context. From a methodological standpoint the use of team-level perceptions can be considered an important strength of the study because mean ratings tend to smooth both random variance in individual responses and systematic differences that may contaminate individual perceptions, such as an individual's background, previous experiences, and personality (Seibert et al. 2004). Thus, the aggregation of perception at the team level of analysis allowed us to develop a more accurate view of the team learning behavior, providing a better understanding of those relationships specified at a level of analysis above the individual, which are rarely considered in the IS literature. Third, all participants in our study used the same new system. Therefore, we were able to capture the set of features embedded in the system. Fourth, our field study involved 268 participants in 48 different teams. This team-level sample size compares favorably with other field studies of teams (e.g., Ancona and Caldwell 1992; Faraj and Sproull 2000).

As with any research, our findings need to be interpreted in light of a few limitations. One limitation is the use of a survey method to measure both dependent and independent variables in the study. Such a design raises the potential for common method bias as participants can engage in hypothesis guessing and social desirability while completing the questionnaire (Podsakoff et al. 2003). We attempted to prevent the occurrence of such issues by following the recommendations of Podsakoff et al. (2003). Specifically, we aimed to reduce concerns of common method bias by (1) using multiple respondents within each team and (2) separating the measurement of trying to innovate and its antecedents via a longitudinal study design. Although the system we examined embodied characteristics that are common to other systems, future research should validate our results in other settings in order to increase the generalizability of our findings. Moreover, the results are based on the European context, suggesting the need for future research in other national and cultural settings. For instance, recent research has shown that the drivers of new technology use vary across cultural contexts (Srite and Karahanna 2006). Finally, since our research focuses on a collaborative system, network externalities may play a role in shaping individuals' behavior. Despite the limitation of not considering potential effects due to network externalities (e.g. the individual perceived value of the system could increase as the number of adopters in the team increases), we think that such effects may be limited in observing behaviors that are *exploratory* in nature. Rather we believe that the effects of network externalities could be more likely to occur when studying individual *use* of the system. Individuals may use the system because of the influence of other members' adoption, but they can limit their use to the day-by-day typical interactions with other team members, without deciding to go the extra-mile in extending their use beyond common purposes.

Practical Implications

Amabile and Khaire (2008) suggest that managers generally have not received much guidance on how to promote innovative endeavors in the workplace. Motivating such behavior is particularly challenging because monetary incentives may prove to be ineffective since managers cannot easily monitor the breadth of features used by their employees. The findings in this research have several key implications for managers.

One direct implication of our research is that managers need to direct their interventions at the team level rather than the individual level. As social structures, teams can provide an environment that shapes and reinforces the way in which employees interact with technology on a daily basis. Thus, efforts to promote innovation with IT need to focus on fostering a team environment that supports such behavior. With a supportive team environment in place, team members can reinforce each others' efforts to innovate with IT. Such a collectively targeted approach circumvents the need to rely on individual differences. Our results show that, on average, employees who are embedded in teams with high team learning behavior are more likely to try to innovate with IT compared to employees who are embedded in teams with low team learning behavior. This happened regardless of the employees' level of personal innovativeness.

Our results also show that personal innovativeness needs to be considered in context. In particular, when the immediate social environment does not support collective efforts to learn, managers need to be careful that innovative efforts, among those with a natural inclination to experiment with technology, are not stifled. We find that at high levels of personal innovativeness, innovative tendencies can be muted if the team environment does not support such activity. This is significant because innovative individuals play an important role as lead users of new technologies. Their efforts can lead to discoveries of more effective ways of using technology to support work and these discoveries can be shared with teammates to enhance the productivity of the team as a whole. Sensitivity to attempts to innovate can be high in team settings because employees' work is interdependent and team members are collectively responsible for team outcomes. Such settings, where teammates' work may be disrupted by attempts at innovation with IT, create interpersonal risk. As a consequence, individuals who are highly innovative may repress the expression of innovation. Teams lose out on a potential source of advantage in the workplace.

Our results pertaining to team learning behavior point to one potential lever which managers can use to promote innovation with technology in the workplace. By developing an environment which encourages initiative taking and learning, managers can intrinsically encourage employees to engage in innovative use of technology and team members can mutually reinforce such behaviors. In fostering such a team environment, managers need to exercise patience with employees and recognize that gains from technology exploration are unlikely to be realized in the short term. As Garvin et al. (2008) suggest, this means that any efforts to foster innovation with technology must dispel fear of failure among employees. Rather, managers should recognize that employees need time to engage in ongoing experimentation with the system, in the hopes that gains will be realized over time. Failure is a natural part of innovation and, thus, emphasis must be placed on experimentation, risk-taking, and mutual sharing of lessons learned (Garvin et al. 2008). Team learning behavior represents an environment that promotes such activities.

Directions for Future Research

Our research findings provide a foundation for future research on user exploration of technology features. First, this research found team learning behavior to be a key driver of user trying to innovate with IT. This suggests that collectively embraced norms and values play a critical role in shaping on how employees deal with technology innovations in the workplace. We had identified team learning behavior as a lever that managers could potentially utilize to foster desirable innovative behavior. However, in this research we did not examine how managers can foster such team contextual dimension. Future research would benefit from studies that uncover the specific behaviors through which managers can shape team learning behavior when new systems are being deployed. Leadership theories may provide a particularly useful lens for understanding relevant behaviors. For instance, the literature on transformational leadership might shed light on the activities through which managers can encourage the development of team learning behavior. Alternatively, the role of coaching can be incorporated into future studies of technology use in teams. Specifically, future research could focus on understanding how team members and team leaders mutually reinforce each other's exploration and use of the technology so as to maximize its benefits.

Having provided evidence of the model's predictive validity, future extensions of this work should examine the influence of other traits which may stimulate individuals' effort in trying to innovate with IT. While we took into account a relatively stable trait which affects individual's behavior in interacting with technology, future research should take into account the effects of less enduring traits (Tierney and Farmer 2002). For example future research could take into account how computer self-efficacy may directly affect individuals' innovation with technology as well as the contextual factors which may activate self-efficacy. When individuals feel like they have the ability to successfully interact with technology, along with an environment which stimulates the expression of such trait, it is likely they would be willing to attempt to innovate with IT. To the extent that less enduring individual differences affect trying to innovate through similar processes (i.e., intrinsic motivation), we expect the team context for learning to have a similar moderating influence.

Our findings, which highlight the joint effect of individual disposition and team context, should stimulate future research to adopt a multilevel approach to examining individuals' technology-oriented behavior. Given the limited amount of research adopting a multilevel lens in this domain, future research could help advance this work by examining team learning behavior, trying to innovate, and task performance over time. In particular, it would be valuable to examine the existence of a feedback loop between learning behavior, trying to innovate, and individual (and, consequently, team) task performance. If individual exploration of a technology yields new insights, the extent to which those insights are shared among team members over time might inform the long term viability of the team's learning behavior, while also yielding task performance gains. Such a feedback loop may even enhance team learning, which has been linked to greater team performance. Such efforts would go a long way in advancing the technology use literature as well as the broader multilevel literature by combining top-down and bottom-up cross-level relationships. Such approaches are lacking in the literature (Kozlowski and Klein 2000; Mathieu and Chen 2010).

Conclusion

In this research, relying on trait-activation theory, we integrated team context studies with technology use research to understand the factors that facilitate user's trying to innovate with IT. We theorized relationships between team learning behavior, PIIT, and trying to innovate. We found that team learning behavior and PIIT have a direct effect on individual trying to innovate. Further, team learning behavior moderates the relationship between PIIT and trying to innovate with IT. Our results show also that under the low team learning behavior contingency, the effect of PIIT on trying to innovate assumes a curvilinear inverted U-shape pattern. Taken together, these findings contribute to the technology use literature through demonstrating the theoretical utility of incorporating levels of analysis other than the individual level when trying to understand individual behaviors with technology.

References

Agarwal, R. 2000. Individual acceptance of information technologies. In R. W. Zmud (Ed.), *Framing the domains of IT management: projecting the future from the past*. Cincinnati, OH, Pinnaflex Educational Resources, 105-127.

Agarwal, R., J. Prasad. 1998. A conceptual and operational definition of personal innovativeness in the domain of information technology. *Information Systems Research* 9(2) 204-215.

Ahuja, M.K., J.B. Thatcher. 2005. Moving beyond intention and toward the theory of trying: Effects of work environment and gender on post-adoption information technology use. *MIS Quarterly* 29(3) 427-459.

Aiken, L.S., S.G. West. 1991. *Multiple Regression: Testing and Interpreting Interactions*. Sage, London.

Amabile, T.M., M. Khaire. 2008. Creativity and the role of the leader. *Harvard Business Review* 86(10) 101-109.

Ancona, D.G., D. Caldwell. 1992. Bridging the boundary: External activity and performance in organizational teams. *Administrative Science Quarterly* 37(4) 634-665.

Anderson, N.R., M.A. West. 1998. Measuring climate for work group innovation: Development and validation of the team climate inventory. *Journal of Organizational Behavior* 19(3) 235-258.

Bagozzi, R.P., P.R. Warshaw. 1990. Trying to consume: Pursuit of goals in consumer behavior. *Journal of Consumer Research* 17(2) 127-141.

Barrick, M.R., Bradley, B.H., Kristof-Brown, A.L, Colbert, A.E. 2007. The moderating role of top management team interdependence: Implications for real teams and working groups. *Academy of Management Journal* 50(3), 544-557.

Bentler, P.M. 1990. Comparative fit indexes in structural models. *Psychological Bulletin 107(22)* 238–246.

Bliese, P.D. 2000. Within-group agreement, non-independence, and reliability: Implications for data aggregation and analysis. In K.J. Klein and S.W. Kozlowski, (Eds.) *Multilevel Theory, Research, and Methods in Organizations*. San Francisco, CA, Jossey-Bass, 349-381.

Bliese, P.D., P.J. Hanges. 2004. Being both too liberal and too conservative: The perils of treating grouped data as though they were independent. *Organizational Research Methods* 7(4) 400-417.

Bunderson, J.S., K.M. Sutcliffe. 2003. Management team learning orientation and business unit performance. *Journal of Applied Psychology* 88 552-560.

Burton-Jones, A., M.J. Gallivan. 2007. Towards a deeper understanding of system use in organizations: A multilevel perspective. *MIS Quarterly* 31(4) 657-679.

Chen, Z., W. Lam, J.A. Zhong. 2007. Leader-member exchange and member performance: A new look at individual-level negative feedback-seeking behavior and team-level empowerment climate. *Journal of Applied Psychology* 92(1) 202-212.

Day, D.V., S.B. Silverman. 1989. Personality and job performance: Evidence of incremental validity. *Personnel Psychology* 42 25-36.

Edmondson, A. C. 1999. Psychological safety and learning behavior in work teams. *Admin. Sci. Quart.* 44(2) 350-383.

Edmondson, A.C. 2002. The local and variegated nature of learning in organizations: A group-level perspective. *Organization Science* 13(2) 128-146.

Faraj, S., L. Sproull. 2000. Coordinating expertise in software development teams. *Management Science* 46(12) 1554-1568.

Fornell, C., D.F. Larcker. 1981. Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research* 18 39-50.

ForresterResearch 2007. Enterprise Collaboration: Hot as Ever in 2008. (http://www.forresterpanel.com/rb/search/results.jsp?N=0+70071+70946, accessed June 20 2010).

Gallivan, M.J., V.K. Spitler, M. Koufaris. 2005. Does information technology training really matter? A social information processing analysis of coworkers' influence on IT usage in the workplace. *Journal of Management Information Systems* 22(1) 153-192.

Garvin, D.A. 1993. Building a learning organisation. *Harvard Business Review* 71(4) 78-92.

Garvin, D.A., A.C. Edmondson, F. Gino. 2008. Is yours a learning organization? *Harvard Business Review* 86(3) 109-116.

Gefen, D., D.W. Straub. 1997. Gender differences in the perception and use of e-mail: An extension to the technology acceptance model. *MIS Quarterly* 21(4) 389-400.

George, J.F., S. Iacono, R. Kling. 1995. Learning in context: Extensively computerized work groups as communities of practice. *Accounting, Management and Information Technology* 5(3-4) 185-202.

Griffith, T. L. 1999. Technology features as triggers for sensemaking. *Academy of Management Review* 24(3) 472-488.

Gupta, S., E. Karahanna. 2004. Technology adoption in complex systems. Paper presented at *Southern Association of Information Systems Conference*, Savannah, GA.

Hackman, J.R. 1987. The design of work teams. In *Handbook of Organizational Behavior,* J. Lorsch (ed.), Englewood Cliffs, NJ: Prentice-Hall, 315-342.

Hair, J.F., R.E. Anderson, R.L. Tatham, W.C. Black. 1998. *Multivariate Data Analysis*, 5th ed., Upper Saddle River, NJ, Prentice Hall.

He, Z.-L., P.-K. Wong. 2004. Exploration vs. exploitation: An empirical test of the ambidexterity hypothesis. *Organization Science* 15 481-494.

Hirst, G., D. van Knippenberg, J. Zhou. 2009. A cross-level perspective on employee creativity: Goal orientation, team learning behavior, and individual creativity. *Academy of Management Journal* 52(2) 280-293.

Hofmann, D. 1997. An Overview of the logic and rationale of hierarchical linear models. *Journal of Management 23*(6) 723-744.

Hu, L.T., P.M. Bentler. 1999. Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling* 6 1-55.

IDC. 2010. *Worldwide ITspending historical databook 2Q10*. Report.

Ilgen, D.R., J.R. Hollenbeck, M. Johnson, D. Jundt. 2005. Teams in organizations: From input-process-output models to IMOI models. *Annu. Rev. Psychol.* 56(1) 517-543.

James, L.R., R.G. Demaree, G. Wolf, 1984. Estimating within-group interrater reliability with and without response bias. *Journal of Applied Psychology* 69(1) 85-98.

James, L.R., L.J. Williams. 2000. The cross-level operator in regression, ANCOVA, and contextual analysis. In *Multilevel Theory, Research, and Methods in Organizations: Foundations, Extensions, and New Directions*, K. J. Klein and S. W. J. Kozlowski (eds.), San Francisco, CA: Jossey-Bass, 382–424.

Jasperson, J., P.E. Carter, R.W. Zmud. 2005. A comprehensive conceptualization of post-adoptive behaviors associated with information technology-enabled work systems. *MIS Quarterly* 29(3) 525-557.

Johns, G. 2006. The essential impact of context on organizational behavior. *Academy of Management Review* 31(2) 386-408.

Karahanna, E., M. Ahuja, J. Galvin, M. Srite. 2002. Individual differences and relative advantage: The case of GSS. *Decision Support Systems* 32(4) 327-341.

Karahanna, E., D.W. Straub, N.L. Chervany. 1999. Information technology adoption across time: A cross-sectional comparison of pre-adoption and post-adoption beliefs. *MIS Quarterly* 23(2) 183-213.

Klein, K.J., F. Dansereau, R.J. Hall. 1994. Levels issues in theory development, data collection, and analysis. *Academy of Management Review* 19(2) 195-229.

Kozlowski, S.W.J., K.J. Klein. 2000. A multilevel approach to theory and research in organizations: Contextual, temporal, and emergent processes. In *Multilevel Theory, Research, and Methods in Organizations: Foundations, Extensions, and New Directions*, K.J. Klein and S.W.J. Kozlowski (eds.), San Francisco, CA: Jossey-Bass, 3–90.

Li, X., J.J. Hsieh. 2007. Impact of transformational leadership on system exploration in the mandatory organizational context. In *Proceedings of the 28th International Conference on Information Systems*, Montreal, Canada. 1-20.

Louis, M.R., R.I. Sutton. 1991. Switching cognitive gears: From habits of mind to active thinking. *Human Relations* 44(1) 55-76.

Magni, M., M.S. Taylor, V. Venkatesh. 2010. To play or not to play? A cross-temporal investigation using hedonic and instrumental perspectives to explain user intentions to explore a technology. *International Journal of Human-Computer Studies* 68 572-588.

Manz, C.C., H.P. Sims. 2001. *The new superleadership: leading others to lead themselves*. New York, NY, Berrett-Koehler Publishers.

Mathieu, J.E., G. Chen. 2010. The etiology of the multilevel paradigm in management research. *Journal of Management*. in press.

Mathieu, J.E., S.R. Taylor. 2007. A framework for testing meso-mediational relationships in organizational behavior. *Journal of Organizational Behavior* 28(2) 141-172.

Medesker, G.J., L.J. Williams, P.J. Holahan. 1994. A review of current practices for evaluating causal models in organizational behavior and human resources management research. *Journal of Management* 20 439-464.

Morgeson, F.P., D.A. Hofmann. 1999. The structure and function of collective constructs: Implications for multilevel research and theory development. *Academy of Management Review* 24(2) 249-265.

Morris, M.G., V. Venkatesh. 2000. Age differences in technology adoption decisions: Implications for a changing work force. *Personnel Psychology* 53 375-403.

Nambisan, S., R. Agarwal, M. Tanniru. 1999. Organizational mechanisms for enhancing user innovation in information technology. *MIS Quarterly* 23(3) 365-395.

O'Leary, M.B., J.N. Cummings. 2007. The spatial, temporal, and configurational characteristics of geographic dispersion in teams. *MIS Quarterly* 31(3) 433-452.

Oreg, S. 2003. Resistance to change: Developing an individual differences measure. *Journal of Applied Psychology* 88(4) 680-693.

Orlikowski, W.J. 1993. Learning from notes: Organizational issues in groupware implementation. *Information Society* 9 237-250.

Orlikowski, W.J., J. Yates, K. Okamura, M. Fujimoto. 1995. Shaping electronic communication: The metastructuring of technology in the context of use. *Organization Science* 6(4) 423-444.

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

Raudenbush, S.W., A.S. Bryk. 2002. *Hierarchical Linear Models: Applications and data analysis methods*. London, UK, Sage Publications Inc.

Rigby, D.K., F.F. Reichheld, P. Schefter. 2002. Avoid the Four Perils of CRM. *Harvard Business Review* 80 (2) 101-109.

Rogers, E.M. 1995. *Diffusion of Innovations*. Free Press, New York: NY.

Ross, J.W., P. Weill. 2002. Six IT Decisions your IT people shouldn't make. *Harvard Business Review* 80 (11) 84-91.

Rousseau, D.M. 1985. Issues of level in organizational research: Multilevel and cross-level perspectives. *Research in Organizational Behavior* 7 1-37.

Rousseau, D.M. 2010. Reinforcing the micro/macro bridge: Organizational thinking and pluralistic vehicles. *Journal of Management*. in press.

Sarker, S., J.S. Valacich. An alternative to methodological individualism: A non-reductionist approach to studying technology adoption by groups. *MIS Quarterly* 34 (4) 779-808

Seibert, S.E., S.R. Silver, W.A. Randolph. 2004. Taking empowerment to the next level: A multiple-level model of empowerment, performance, and satisfaction. *Academy of Management Journal* 47 332-349.

Shalley, C.E., J. Zhou, G.R. Oldham. 2004. The effects of personal and contextual characteristics on creativity: Where should we go from here? *Journal of Management* 30 933-958.

Snijders, T.A.B., R.J. Bosker. 1999. *Multilevel Analysis: An Introduction to Basic and Advanced Multilevel Modeling*, London, UK: Sage.

Spender, J.C., E.H. Kessler. 1995. Managing the uncertainties of innovation: Extending Thompson (1967). *Human Relations* 48(1) 35-56.

Srite, M., E. Karahanna. 2006. The role of espoused national cultural values in technology acceptance. *MIS Quarterly* 30(3) 679-704.

Sun, H., P. Zhang. 2006. Role of moderating factors in user technology acceptance. *International Journal of Human-Computer Studies* 64(2) 53-78.

Taggar, S. 2002. Individual creativity and group ability to utilize individual creative resources: A multilevel model. *Academy of Management Journal* 45 315-330.

Tett, R.P., D.D. Burnett. 2003. A personality trait-based interactionist model of job performance. *Journal of Applied Psychology* 88(3) 500-517.

Tett, R.P., H.A. Guterman. 2000. Situation trait relevance, trait expression, and cross-situational consistency: Testing a principle of trait activation. *Journal of Research in Personality* 34 397-423.

Thatcher, J.B., P.L. Perrewe. 2002. An empirical examination of individual traits as antecedents to computer anxiety and computer self-efficacy. *MIS Quarterly* 26(4) 381-396.

Thomke, S. 1998. Managing experimentation in the design of new products. *Management Science* 44 743-762.

Tichy, N.M. 1983. *Managing Strategic Change: Technical, Political, and Cultural Dynamics*. Wiley.

Venkatesh, V., S.A. Brown, L.M. Maruping, H. Bala. 2008. Predicting different conceptualizations of system use: The competing roles of behavioral intention, facilitating conditions, and behavioral expectation. *MIS Quarterly* 32(3) 483-502.

Venkatesh, V., F.D. Davis, M.G., Morris. 2007. Dead or alive? The evolution, trajectory, and future of technology adoption research. *Journal of the Association for Information Systems* 8(4) 267-286.

Venkatesh, V., L.M. Maruping, S.A. Brown. 2006. Role of time in self-prediction of behavior. *Organizational Behavior and Human Decision Processes* 100(2) 160-176.

Venkatesh, V., M.G. Morris. 2000. Why don't men ever stop to ask for directions? Gender, social influence, and their role in technology acceptance and usage behavior. *MIS Quarterly* 24(1) 115-139.

Venkatesh, V., M.G. Morris, G.B. Davis, F.D. Davis. 2003. User acceptance of information technology: Toward a unified view. *MIS Quarterly* 27(3) 425-478.

Vera, D., M. Crossan. 2005. Improvisation and innovative performance in teams. *Organization Science* 16(3) 203-224.

Wageman, R. 1995. Interdependence and group effectiveness. *Administrative Science Quarterly* 40 145-180.

Wilkens, R., M. London. 2006. Relationships between climate, process, and performance in continuous quality improvement groups. *Journal of Vocational Behavior* 69(3) 510-523.

Yi, M.Y., J.D. Jackson, J.S. Park, J.C. Probst. 2006. Understanding information technology acceptance by individual professionals: Toward an integrative view. *Information & Management* 43 350-363.

Zhang, X.M., K.M. Bartol. 2010. Linking empowering leadership and employee creativity: The influence of psychological empowerment, intrinsic motivation, and creative process engagement. *Academy of Management Journal* 53(1) 107-128.