AN INVESTIGATION OF THE ANTECEDENTS AND CONSEQUENCES OF TEAM MEMBERS' EXTERNAL LEARNING: A BOTTOM-UP MODEL

CHUDING LING

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The Hong Kong Polytechnic University

Department of Management and Marketing

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Chuding Ling

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CERTIFICATE OF ORIGINALITY

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ABSTRACT

External learning is an increasingly prevalent activity engaged in by the members of teams that has important implications for team and organizational effectiveness. Despite this prevalence and importance, limited studies have been conducted examining the social structural factors that lead to individual task versus contextual learning along with how the team-level performance implications emerge after individual team members engage in task versus contextual learning. To address these research questions, I conduct three studies. In Study 1, I draw upon social network theory and investigate why and when individuals engage in task versus contextual learning. Specifically, I propose and establish that the density of an individual's external network is positively related to the individual's task learning, while the betweenness centrality of an individual in his/her external network is positively associated with the individual's contextual learning. I further argue and find that the individual's knowledge depth strengthens the positive association between density and task learning. In contrast, I propose and reveal that an individual's knowledge breadth magnifies the positive relationship between betweenness centrality and contextual learning.

In Study 2 and Study 3, I draw upon the framework of team receptivity to personnel movement and investigate how and when the different types of knowledge acquired by a team member's task versus contextual learning are disseminated within teams and further integrated into team performance. On top of this theoretical framework, I develop a multilevel conceptual model that uncovers the presumed processes underlying the relationships between individual team member's different forms of external learning and team performance. More specifically, I propose and find that Member A's task learning is positively and indirectly associated with Member B's task knowledge utilization through Member A's task knowledge sharing, while Member A's contextual learning is positively and indirectly related to Member B's team work reflexivity through Member A's contextual knowledge sharing. Furthermore, I argue and find that a higher density of task knowledge utilization and/or team work reflexivity among team members contributes to a better team performance. Lastly, based upon the team receptivity framework and associated empirical research, I introduce team performance pressure as a theory-relevant moderator which strengthens the linkages between task learning, task knowledge sharing, and task knowledge utilization.

The findings from the three studies primarily suggest that task learning and contextual learning differ in terms of both their antecedents and consequences. The implications of this dissertation for theory and practice are also discussed.

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CHAPTER 1: INTRODUCTION

Research Background

With the emergence of new organizational forms such as boundaryless, network-based, and platform organizations, teams are increasingly being adopted by progressively more companies to undertake complex cross-functional tasks and bridge disconnected organizations in support of value creation (e.g., Mathieu, Gallagher, Domingo, & Klock, 2019; Mathieu, Hollenbeck, van Knippenberg, & Ilgen, 2017). For example, according to the “Big Platform and Smart Frontend” approach implemented by the Merchant Services Division of the Alibaba Group, hundreds of frontends (i.e., semi-autonomous and self-managing teams) have been established and empowered to provide professional services regarding techniques and marketing for the merchants operating on the Alibaba trading platform (Boston Consulting Group, Ali Research, & Baidu Development Research Center, 2019; Boston Consulting Group & Ali Research, 2016). Similarly, in the microdivisionalization business model created and adopted by the Haier Group, there are thousands of self-ownership entities (i.e., business unit-like entrepreneurial teams) operating in the organization, which assume responsibility for their own performances by obtaining orders from extra-organizational entities and configuring resources within the organization to fulfill orders (Luo, van de Ven, Jing, & Jiang, 2018; Meyer, Lu, Peng, & Tsui, 2017).

As these examples illustrate, work teams are no longer closed systems nested within a host organization. Instead, they operate as open systems that frequently interact with other entities inside and outside of the organization (e.g., Drach-Zahavy & Somech, 2010; Kouchaki, Okhuysen, Waller, & Tajeddin, 2012). As a result of this expanding scope of interaction, work teams are increasingly facing challenges such as environmental volatility, external dependency, task complexity, and resource scarcity (e.g., Choi, 2002; Thompson, 1967). In order to overcome these challenges, team members are compelled to learn — intensively, effectively, and rapidly. Recently, both researchers and practitioners have recognized that teams cannot rely solely upon internal learning to generate all the necessary resources and knowledge; instead they often need to engage in external learning, or "*interpersonal knowledge acquisition, sharing, and combination activities with individuals external to the group*" (Wong, 2004: 646). Effective external learning is deemed to not only predict team effectiveness, but also to act as a critical source of competitive advantage for organizations (Ancona & Bresman, 2006; Haas, 2006; Peltokorpi & Hasu, 2015).

Given the significant implications of external learning for team and organizational effectiveness, studies on this topic have burgeoned in recent years. With the flourishing of this literature, scholars have realized that team members may engage in different types of external learning that have different purposes and functions (e.g., Edmondson, 2002). In this regard, by integrating the literatures of knowledge transfer and boundary spanning, Bresman and colleagues (Bresman, 2010, 2013; Harvey, Bresman, & Edmondson, 2018) conceptualized and validated a two-dimensional model of external learning. The first type of external learning refers to *task learning*, which emphasizes learning from organizational members who are external to the focal team and yet possess similar experiences concerning the key aspects of the tasks undertaken by the focal team. The second type is *contextual learning*, which consists of activities that emphasize learning from organizational members who are external to the focal team and have knowledge about the key aspects of the organizational context in which the focal team operates (Bresman, 2010; Harvey et al., 2018). Though the two forms of external learning are different in terms of the content of the knowledge acquired, both are considered to enhance team performance.

Research Needs and Objectives

In spite of the significant contributions made by the previous literature, the research on external learning is still in its infancy and several lines of inquiry merit further exploration. In particular, although the seminal work of Bresman and others (Bresman, 2010, 2013; Harvey et al., 2018) conceptualized the two-dimensional model of external learning, it did not provide the theoretical underpinnings of this model. In addition, perhaps because a theoretical account of the differences between task versus contextual learning in the nomological network is lacking, the current literature in this research domain has mainly focused upon one type of external learning and seldom investigated task and contextual learning simultaneously (e.g., Luan, Rico, Xie, & Zhang, 2016; Wong, 2004). By taking such an undifferentiated approach, the research has not explored whether different antecedents may lead to distinct forms of external learning, nor has it examined whether different forms of external learning are likely to stimulate the same or different processes that lead to team performance.

The adoption of this undifferentiated approach has been unfortunate. Indeed, without depicting the different antecedents and consequences that lead to different forms of external learning, we are not able to understand the theoretical question concerning the causes and effects of task versus contextual learning or the practical question of how teams may be able to reap the most benefits from these different forms of external activities (e.g., Marrone, 2010). For this reason, the primary research need I aim to fill with this dissertation is to understand the different antecedents and consequences associated with task versus contextual learning, thereby, establishing evidence for the validity of the two-dimensional model of external learning in the nomological network.

Driven by the primary research need, I have two specific research objectives to address within this dissertation. The first is to understand why and when a team member would engage in task versus contextual learning. Although prior studies have revealed that motivational factors are important in facilitating the external learning of team members, we know little about how social structural factors promote or limit individuals' opportunities to engage in different forms of external learning (e.g., van Wijk, Jansen, & Lyles, 2008). This is important given that in many cases the absence of external learning is not the result of a lack of motivation among individuals, but rather the fact that an individual is constrained by the limited opportunities embedded in his/her social structure. The second objective is to investigate how and when the different types of knowledge acquired by a team member's external learning are disseminated within teams and further integrated into the team performance. This is worth exploring because the processes concerning how team-level performance implications emerge from individual team members' different forms of external learning have always been assumed but seldom investigated (e.g., Marrone, 2010).

Before addressing the aforementioned two research questions, however, I firstly shift the unit of analysis within which external learning is conceptualized and operationalized from a team level to an individual level. Although most studies in this research domain have conceptualized and operationalized external learning as team-level constructs with a referent-shift model (Chan, 1998), external learning behaviors are activities essentially undertaken by individual members on behalf of a team. Moreover, as Marrone (2010) notes, the individual behavioral contributions to a team's external learning may or may not be isomorphic or converge among members. Instead, they may vary in amount and type depending on the characteristics of the team members as well the task and team interdependencies that exist among them. In fact, previous studies on other forms of external activities at individual level (e.g., inter-team coordination) have revealed that different individuals may have different numbers of opportunities to engage in externally oriented behaviors as a result of the particular characteristics that different individuals possess (e.g., de Vries, Walter, van der Vegt, & Essens, 2014). Similarly to this, I argue that the conceptualization and operationalization of external learning should also be shifted from a team level to an individual level, as this shift would better align the concept with the phenomenon in the real workplace. After clarifying the rationale behind shifting the analysis level of the two forms of external learning and with the two research questions in mind, I briefly introduce the present dissertation in the following.

The Present Dissertation

To better understand the antecedents and consequences of the different forms of external learning engaged in by an individual team member, I conducted three studies within the present dissertation, which constitute the overall conceptual model depicted in Figure 1.

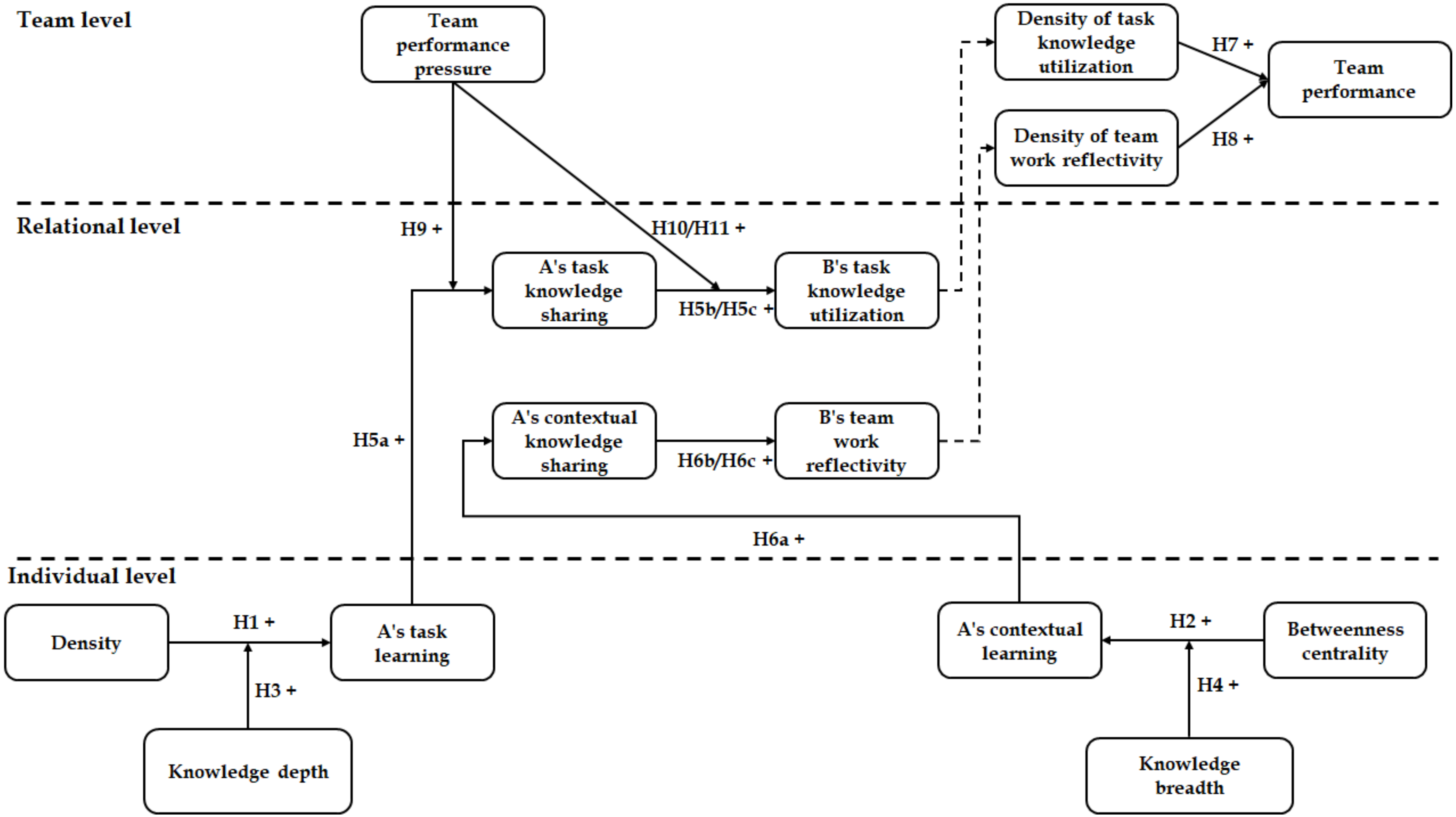

Figure 1. The overall conceptual model of the dissertation

In Study 1, I draw upon social network theory and investigate why and when a team member would engage in task versus contextual learning. Specifically, the key tenet of social network theory suggests that the configurations of social relationships surrounding a node could enable and limit the node's opportunities to acquire, transfer, and create knowledge (e.g., Phelps, Heidl, & Wadhwa, 2012). On top of this tenet, I propose and explicate that the density of an individual's external network is positively related to the individual's task learning, while the betweenness centrality of an individual within his/her external network is positively associated with the individual's contextual learning. Social network research also highlights the important role of individual attributes (e.g., the characteristics of individuals' knowledge structures) in realizing and mobilizing the resources available through network configurations (e.g., Baer, 2010; Reinholt, Pedersen, & Foss, 2011). As such, I further argue that the depth of an individual's knowledge strengthens the positive association between density and task learning. In contrast, I also propose that an individual's knowledge breadth magnifies the positive relationship between betweenness centrality and contextual learning.

In Study 2 and Study 3, I draw upon the framework of team receptivity to personnel movement and attempt to investigate how and when the different types of knowledge acquired by a team member's external learning are disseminated within teams and further integrated into team performance. The team receptivity framework is a relevant and useful theoretical perspective that has been adopted by previous studies to understand the processes and performance implications associated with personnel movement in teams (e.g., Gruenfeld, Martorana, & Fan, 2000; Kane & Rink, 2017; Rink, Kane, Ellemers, & van der Vegt, 2017). The key tenet of the team receptivity framework posits that a particular team member's movement across a team boundary (e.g., external learning) may lead another member in the same team to utilize the provided new knowledge and/or trigger another member to reflect upon the current work in the team. In this literature, these two processes are referred to as task knowledge utilization and team work reflexivity, respectively.

On top of this theoretical framework, I develop a multilevel conceptual model that discloses the presumed processes underlying the relationships between the external learning of individual team members and team performance. More specifically, I propose that Member A's task learning is positively and indirectly associated with Member B's task knowledge utilization through Member A's task knowledge sharing, while Member A's contextual learning is positively and indirectly related to Member B's team work reflexivity through Member A's contextual knowledge sharing. Furthermore, I argue that a higher density of task knowledge utilization and/or team work reflexivity among team members contributes to a better team performance. Lastly, drawing upon the team receptivity framework and associated empirical research (e.g., Choi, 2002; Rink et al., 2017), I introduce team performance pressure as a theory-relevant moderator which strengthens the linkages among task learning, task knowledge sharing, and task knowledge utilization.

Research Contributions

I seek to make several contributions through this dissertation. First, I advance the literature on external learning by highlighting the distinctions between task and contextual learning in terms of their antecedents and consequences. Despite the seminal advance made by Bresman (2010) in conceptualizing task learning versus contextual learning, it did not provide a theoretical account for the taxonomy of the two-dimensional model. By adopting social network theory and the team receptivity framework, I attempt to reveal that different forms of external learning are linked to different types of antecedents and consequences, respectively. As such, I advance the theoretical underpinnings of the classification of external learning by demonstrating that task learning is different from contextual learning in its causes as well as its functions.

Secondly, I advance our understanding of why and when a team member would engage in different forms of external learning from a social network perspective. Although previous studies drawing on various theoretical perspectives have highlighted the motivational factors that facilitate individuals' external learning behaviors (e.g., Bresman & Zellmer-Bruhn, 2013), I propose and argue that in many circumstances the absence of external learning is not the result of a lack of motivation among the individuals, but rather that the individual is constrained by the limited opportunities embedded in his/her social structure or the inappropriate knowledge structure possessed by him/her to utilize the opportunities within the social structure. My findings suggest that external network density, when complemented with knowledge depth, present the best prospect for a team member to engage in task learning. Meanwhile, betweenness centrality in the external network when coupled with knowledge breadth will render it most likely that a team member will engage in contextual learning.

Thirdly, I advance the literature on the consequences of the external learning of individual team members on team performance. Though extant theoretical and empirical works have repeatedly suggested that external learning is beneficial for team effectiveness by importing necessary knowledge and resources, the processes underlying that learning have always been assumed but seldom investigated (e.g., Marrone, 2010). By drawing upon the team receptivity framework and asserting a bottom-up model, I address this significant gap by first delineating the interactions occurring in the dyads between Member A who engages in external learning and knowledge sharing and Member B who exhibits receptive reactions towards Member A’s behaviors, and further link the relational-level interactions to team performance. As such, I advance the literature by clarifying the previously assumed processes concerning how and when the knowledge acquired by an individual team member’s external learning is disseminated and integrated into team performance.

Lastly, this dissertation also has several implications for social network theory and the team receptivity framework, respectively. On one hand, by proposing the moderating role played by the characteristics of individuals' knowledge structures on the social network configurations–external learning relationships, I advance social network theory by adding to an expanding body of literature that highlights the agency of individuals in realizing the utilities of social positions with advantages. Moreover, by revealing that density and betweenness centrality may facilitate different forms of external learning, I confirm the notion that closure (e.g., density) and brokerage (e.g., betweenness centrality) could exist simultaneously and have complementary effects on knowledge management outcomes (e.g., Reagans & McEvily, 2008). On the other hand, by applying the team receptivity framework to tackle the effects of task versus contextual learning with a multilevel model, I enrich the framework with a more precise picture of the kinds of knowledge involved in the theoretical scope. Moreover, the introduction and identification of team performance pressure as a new and important moderator also extends our understanding of the boundary conditions of the team receptivity framework.

This dissertation also has some implications for practitioners. First, the findings from Study 1 initiate the possibility of more team members being involved in external learning since team members privileged in either a dense advice network or central advice positions can be encouraged to participate. In addition, by revealing the moderating role of knowledge depth and breadth, I highlight to team members the value of the knowledge structure complementing the social structure in materializing the informational utilities that are associated with their position in the external network. Moreover, the findings from Study 2 and Study 3 generally demonstrate that task knowledge utilization and team work reflexivity are the key mechanisms through which task learning and contextual learning relate to team performance. Given this, I suggest that managers pay more attention to whether team members have disseminated and integrated knowledge related to the task in hand or the environment outside the boundary. Moreover, managers can make use of team performance pressures to boost the motivation of team members to utilize the shared knowledge.

CHAPTER 2: LITERATURE REVIEW

The Conceptualization of External Learning: A Historical Overview

The literature on external learning in team contexts can be traced back to two streams of research on small groups in organizations. The first stream of research concerns team boundary spanning, which commenced with Allen and Cohen's (1969) pioneering work. Within this stream of literature, scholars have treated teams as open systems and acknowledged that teams cannot rely solely upon themselves to generate all the resources they require; instead they need to engage in boundary spanning in order to obtain important information and feedback (e.g., Aldrich & Herker, 1977; Allen & Cohen, 1969; Tushman, 1977). Building on this earlier work, Ancona and Caldwell (1992) proposed boundary spanning behaviors to be a set of activities carried out by team members in order to manage the external environment beyond their own teams, which include ambassador activities, task coordination activities, and scout activities. Among these, scout activities involve team members' efforts to seek environmental information regarding technological innovations, marketing competition, and other aspects of the general environment outside of their own teams, which have been deemed as one conceptual source of external learning (Harvey et al., 2018).

The second stream of research concerns group learning and knowledge transfer, which began with Argote et al.'s studies on team learning curves (e.g., Argote & Ingram, 2000; Darr, Argote, & Epple, 1995). Although these studies did not explicitly reveal the behavioral underpinnings involved in these activities, they did suggest that learning transfers among the subunits (i.e., teams) within the same organization, especially with regard to how to better perform tasks, can greatly enhance the performance of these subunits (e.g., Argote, 2015; Argote & Fahrenkopf, 2016; Argote & Ingram, 2000). Furthermore, research has shown that teams were able to obtain the relevant experience to solve problems through their meaningful interactions with other teams who have trodden similar paths, thereby, obtaining a higher rate of learning and better task performance. Argote et al. (Argote & Fahrenkopf, 2016; Argote & Ingram, 2000) refer to the processes through which an organizational unit learns from or is affected by the experience of another organizational unit as knowledge transfer, which is believed to be another conceptual underpinning of external learning (Harvey et al., 2018).

As far as I know, Wong (2004) is the earliest study formally introducing the concept and definition of external learning. In this study, the author distinguished local learning from distal learning with regard to where the team learning (i.e., knowledge acquisition, sharing and combination activities by team members) occurred. Local learning is the activity which is usually referred to as team (internal) learning in the literature (Edmondson, 1999). Distal learning is actually the external learning upon which I focus in this dissertation, which is formally defined as "*interpersonal knowledge acquisition, sharing, and combination activities with individuals external to the group*" (Wong, 2004: 646). In this regard, the scale of distal learning used by Wong (2004) was adapted from the measure of the scouting activities dimension of boundary spanning behaviors that was developed by Ancona and Caldwell (1992). Despite the great advances made by Wong (2004), this study assumed an undifferentiated approach and failed to capture the fact that people may engage in external learning for different purposes and functions (e.g., Edmondson, 2002).

This significant gap was subsequently addressed by Bresman and colleagues (Bresman, 2010, 2013; Harvey et al., 2018). By integrating the two streams of literature I described above (i.e., boundary spanning and knowledge transfer), Bresman (2010) conceptualized and validated a two-dimensional model of external learning. The first type of external learning refers to *task learning*, which emphasizes learning from organizational members who are external to the focal team and yet possess similar experiences about the key aspects of the tasks of the focal team. The second type is *contextual learning*, which is comprised of activities that emphasize learning from organizational members external to the focal team who have knowledge of the key aspects of the organizational context in which the focal team operates (Bresman, 2010; Harvey et al., 2018). According to Bresman and colleagues' conceptualization, the two forms of external learning share some conceptual commonalities. More specifically, both forms of external learning are targeted at entities outside of the team boundaries, and the knowledge obtained by both forms is assumed to be new and useful to the focal team and cannot be easily generated by the focal team. Moreover, both forms of external learning are deemed to benefit the focal team, though in different ways (Bresman, 2010, 2013; Harvey et al., 2018). In spite of these commonalities, the two forms of external learning differ from each other in three ways, which are displayed in Table 1 and elaborated upon in the following.

First, they differ in terms of the nature of the knowledge obtained. Task learning focuses upon the acquisition of similar experiences concerning the key aspects of the tasks in the focal team. A substantial amount of procedural knowledge—which is rich and complex— would also be involved in the learning process. In contrast, contextual learning emphasizes the absorption of information concerning the key aspects of the context in which the focal team operates. The knowledge involved in this learning process is mainly declarative, which is simple and straightforward.

Second, the two forms of external learning differ in their purposes and functions. The aim of task learning is to use the key lessons learned externally to avoid repeating mistakes, to skip unnecessary steps, and to avoid reinventing the wheel. In other words, task learning aims to perform actions correctly and improve the *efficiency* of the team work. However, the purpose of contextual learning is to develop a collective understanding of the competitive context and the threats and opportunities hidden within the background. To put it another way, its purpose is to perform actions correctly and improve the *effectiveness* of the team work.

Finally, task learning is distinct from contextual learning in respect to the characteristics of the interactions. As described above, task learning focuses upon the acquisition of knowledge from others with similar experiences, thus, the target is specific. What is more, because the knowledge associated with task learning is rich and complex, it usually requires direct and intensive interaction between the two parties involved in the learning. Conversely, contextual learning emphasizes the absorption of information about the key aspects of the context in which the focal team operates, thus, anyone able to provide the contextual information may be the target. Accordingly, direct interaction between the two parties involved in the learning may not be intensive or even necessary.

Table 1. A Comparison of Task and Contextual Learning

	Task Learning	Contextual Learning
Commonalities	● The sources of external learning are entities outside of team boundaries. ● The information obtained by external learning is assumed to be new and useful to the focal team and cannot be easily generated by the focal team. ● Both forms of external learning benefit the focal team, though in different ways.	
Distinctions		
1. Nature of knowledge obtained	● Similar experiences about the key aspects of tasks in the focal team. ● Most are procedural; rich, and complex.	● Information about the key aspects of the context in which the focal team operates. ● Most are declarative; simple and straightforward.
2. Purposes and functions	● Use the key lessons learned to avoid repeating mistakes, to skip unnecessary steps and to avoid reinventing the wheel. ● Perform actions correctly and improve the efficiency of their team work.	● Develop a collective understanding of the competitive context and the threats and opportunities hidden in the background. ● Perform actions correctly and improve the effectiveness of their team work.
3. Characteristics of interaction	● Specific target with similar task experience. ● Needs direct and intensive interaction between the two parties involved in the learning.	● Any target that can provide the contextual information. ● Direct interaction between the two parties involved in the learning may not be intensive or even necessary.

Note. This table is based upon Bresman and colleagues' (2010, 2013; Harvey et al., 2018) conceptualization.

Antecedents of External Learning

Antecedents of task learning. Given that the concept and measurement of task learning have only recently been developed, as far as I am aware, no study has directly investigated its antecedents. However, as alluded to above, the conceptualization of task learning is rooted in the literature on group learning and knowledge transfer within organizations. In this respect, some studies have explored the factors that would facilitate teams in acquiring task-relevant knowledge from the outside of team boundaries. By reviewing the current literature, I found that most studies have focused on the social network characteristics within organizations.

Since the introduction of Argote and Ingram's (2000) conceptualization of knowledge transfer as a basis for the competitive advantage of firms, the investigation of social network characteristics as the antecedent of knowledge transfer has flourished. The increasing evidence has suggested that the positional and structural characteristics of units in organizations (e.g., centrality), the dyadic characteristics between two units (e.g., tie strength) and the organization-wide structural characteristics (e.g., within-organization centralization) have substantial influences on the knowledge transfer of units within organizations. A meta-analysis by van Wijk et al. (2008) and a qualitative review by Phelps et al. (2012) have provided comprehensive summaries of the relevant literature. Here, I only highlight some of the key findings from the literature.

Firstly, at the node or unit level, previous studies have suggested that a high level of centrality within the whole network and of density in a unit's ego network both ensure the focal unit is able to access and obtain more knowledge with less distortion, thereby, easing the knowledge transfer (e.g., Hansen, 1999, 2002). Secondly, at the dyadic level, the high level of tie strength between two units indicates that the interaction in the dyad is intensive, which makes effective knowledge transfer possible (e.g., Schulz, 2003). Lastly, at a more macro level, Tsai (2002) revealed that a centralized structure may prohibit knowledge transfer by stifling the discretion and willingness of a unit to engage in such activities. In spite of the substantial advances made by this literature, the studies reviewed above have mainly focused their analyses upon the external network at the organizational unit level. Thus far, few studies have explored how the social network ties that cross-team boundaries influence the acquisition of task-relevant knowledge from the outside by individual team members. However, as one form of the boundary spanning behaviors engaged in by individual team members, external learning activities transfer the information and knowledge from the outside to the inside of the team boundary. As such, how a team member is connected with contacts outside the team boundary may have a substantial influence upon his/her opportunities to engage in external learning. Unfortunately, prior studies have omitted the connection between cross-boundary ties and external learning.

Antecedents of contextual learning. Compared to that of task learning, there are more studies on the antecedents of contextual learning. This is likely to be because the conceptualization of contextual learning is rooted in the literature on team boundary spanning, or more specifically, scouting activities, which have a longer history and an established scale for measuring these behaviors has already been presented. In reviewing the current literature, I found that the studies on the antecedents of contextual learning extend from an organizational context to team-level factors. Here, I summarize the key findings from the literature.

First, previous studies have suggested that the structural conditions at the organizational level influence team-level contextual learning. More specifically, Bresman and Zellmer-Bruhn (2013) found that organizational structures; or the extent to which roles are specialized, individuals are grouped into hierarchies, and procedures are formalized within organizations (e.g., Bunderson & Boumgarden, 2010); stifle team members' external learning (measured as scouting activities). Conceptually and empirically, the authors explicated that this was due to the decreased task autonomy felt by team members. Moreover, Somech and Khalaili (2014) revealed that inter-team goal interdependence was positively related to a focal team's scouting activities. This was because the high inter-team goal interdependence suggested that the focal team's achievement of a goal was interconnected with other teams, which impelled the members from the focal team to engage in scouting activities.

Second, team-level compositional factors and emergent states have been linked to scouting activities or contextual learning. In particular, previous studies have suggested that a team's functional diversity could be a valuable contribution to team-level scouting activities because a high level of functional diversity indicates team members have diverse connections with others outside of the focal team (e.g., Keller, 2001; Somech & Khalaili, 2014). Moreover, Woolley, Bear, Chang, and DeCostanza (2013) found that when environmental information was necessary for a team, a defensive team strategic orientation was beneficial for the team performance by increasing members' perceptions of the problem scope and facilitating a process-focused work strategy.

In addition, team structure; or the perception that the roles are specialized, individuals are grouped into hierarchies, and procedures are formalized within teams (e.g., Bunderson & Boumgarden, 2010); was found to be positively related to contextual learning. Conceptually and empirically, the authors explicated that this was due to the increased psychological safety felt by team members (Bresman & Zellmer-Bruhn, 2013). Another two studies at team level suggested a more complex relationship between team emergent states and contextual learning. More specifically, Wong (2004) argued for a curvilinear relationship (inverted U-shape) between team cohesion and contextual learning though the empirical findings did not support this hypothesis. Similarly, Luan et al. (2016) revealed that the relationship between a collective team identification and contextual learning was an inverted U-shape when team psychological safety was lower. Both of the studies drew on social identity theory (Tajfel & Turner, 1986), which suggests that a level of identification that is too low makes members less motivated, while a level of identification that is too high leads members to be resistant to learning from the outside.

Consequences of External Learning

Although previous studies have linked task versus contextual learning to various outcomes, including team performance, efficiency, and innovation, the findings are a little different for the two forms of external learning. Generally, contextual learning has a more straightforward main effect on team outcomes, while task learning is subjected to some contingent factors. For example, in the seminal work by Wong (2004), contextual learning was revealed to be positively related to team innovation. Moreover, Bresman (2010) found that contextual learning had a positive relationship with team performance. However, in the same study, the author revealed that the effects of task learning on team performance were positive only when the team's internal learning was high (Bresman, 2010). Similarly, Haas (2006) found that a team's acquisition of task knowledge was beneficial for the team performance when the team had the ability to process the knowledge gathered from the outside, which was further determined by slack time, organizational experience, and the decision-making autonomy possessed by the team.

Despite the fact that the effects of contextual learning are straightforward while the effects of task learning are more dependent on the contingent factors, the main argument for the positive effects of both forms of external learning is similar. That is, by engaging in external learning, teams are able to exchange information with interdependent work units as well as seek feedback and acquire the resources necessary for completing team tasks, both of which would be beneficial for teams in executing team processes and performing more effectively (Joshi, Pandey, & Han, 2009; Marrone, 2010). Contrasting with the repeatedly documented main or moderated effects of team external learning, I know of only two studies that have indirectly assessed which mediator links team external activities and team performance. Drawing on Marks, Mathieu, and Zaccaro's (2001) conceptualization of team processes, Mathieu, Maynard, Taylor, Gilson and Ruddy (2007) proposed a general internal team process consisting of planning work, coordinating efforts, and managing interpersonal relations as the mediator linking the external activities and team performance in a sample of customer service teams. Similarly, sampling software development teams in information technology firms, Faraj and Yan (2009) argued that team psychological safety is the mechanism through which team external activities relate to team performance. However, neither study demonstrated any empirical support for their mediation arguments, leaving the mechanisms underlying team external learning and team effectiveness as open questions.

Conclusions of Literature Review

According to the literature review above, research on external learning is still in its early stages and contains several lines of inquiry that merit further exploration. First, excepting the work of Bresman and colleagues (Bresman, 2010; Harvey et al., 2018), most of the studies in this research domain have only focused upon one type of external learning and seldom investigated task and contextual learning simultaneously. Although Bresman (2010) presented the two-dimensional model of external learning, the theoretical underpinnings of this model were not provided, nor did his study examine whether the two forms of external learning differ in terms of their antecedents and consequences. Thus, more studies are needed to establish the validity of the two-dimensional model in the nomological network.

Second, most of the studies on the antecedents and consequences of a specific type of external learning have conceptualized it as a team-level construct, which ignores the fact that the individual behavioral contributions to team external learning may or may not be isomorphic or converge among members. Therefore, to better align the concept with the phenomenon in the real workplace and to better understand the antecedents and consequences of the two forms of external learning, we need to shift the unit of analysis downwards such that external learning is conceptualized and operationalized from a team level to an individual level.

Third, no study has directly investigated the antecedents of task learning though there is a line of inquiry concerning the social network determinants of knowledge transfer. However, this stream of literature on social networks and knowledge transfer has mainly focused upon analyses at unit level, with few studies exploring how the social network ties that cross-team boundaries influence the acquisition of task-relevant knowledge from the outside by individual team members. Moreover, most studies on the antecedents of a specific type of external learning have mainly focused upon the role of motivational factors (e.g., psychological safety) as an important driver for team members to engage in external learning. Though this line of inquiry on motivational drivers is informative, it has omitted the factors associated with the opportunities that would enable or constrain an individual to engage in external learning. In many cases, the absence of external learning is not the result of a lack of motivation among team members but rather that an individual is constrained by the limited opportunities embedded in his/her social structure for external learning. As such, we need to investigate more of the social structural factors associated with an individual's opportunities to engage in task learning or contextual learning.

Finally, most of the studies on the consequences of a special type of external learning have consistently revealed that such external activities are positively related to collective outcomes such as team performance and team innovation. The main argument of this research is that external learning enables teams to exchange information with interdependent work units as well as seek feedback and acquire the resources necessary for completing team tasks, both of which would be beneficial in executing team processes and performing more effectively. Contrasting with the repeatedly documented main effect of team boundary spanning behaviors, we know little about how the team-level performance implications emerge from the external learning of individual team members. For this reason, more effort is needed to delineate how and when the different types of knowledge acquired by the external learning of individual team members are disseminated within teams and further integrated into team-level performance through a bottom-up process.

CHAPTER 3: STUDY 1

With more organizations being confronted with challenges such as knowledge deficiency, environmental volatility, time pressures, and resource scarcity, both practitioners and researchers have increasingly recognized the fact that teams can no longer rely solely on their internal resources but must engage in external learning (e.g., Argote, Gruenfeld, & Naquin, 2001; Edmondson, Winslow, Bohmer, & Pisano, 2003). External learning, or "*interpersonal knowledge acquisition, sharing, and combination activities with individuals external to the group*" (Wong, 2004: 646), has been found to facilitate the acquisition of incremental information and knowledge beyond the combined resources offered by internal team members aimed at achieving collective objectives and superior performance (Ancona & Bresman, 2006; Haas, 2006; Peltokorpi & Hasu, 2015).

Prior research has commonly adopted a multifaceted view suggesting that team members may engage in different forms of external learning. In particular, by integrating the literatures of knowledge transfer and boundary spanning, Bresman and others (Bresman, 2010, 2013; Harvey et al., 2018) have conceptualized and validated a two-dimensional model of external learning. The first type of external learning refers to *task learning*, which emphasizes learning from organizational members who are external to the focal team and yet possess similar experiences with regard to key aspects of the tasks of the focal team. The second type is *contextual learning*, which pertains to activities that emphasize learning from organizational members who are external to the focal team and have knowledge about key aspects of the organizational context within which the focal team operates (Bresman, 2010; Harvey et al., 2018). Therefore, the two forms of external learning are conceptually distinct with regard to the *content* of the knowledge acquired, with task learning focusing on the acquisition of similar task experiences and contextual learning emphasizing the absorption of nonredundant information regarding the external context. Empirically, the two forms of external learning have also been found to contribute to team effectiveness in different ways.

Given the great value of external learning for team effectiveness and the differences associated with different forms of external learning, an important research question that warrants further examination is how team members can maximize their task and contextual learning. As far as I know, not many studies have directly investigated this question (e.g., Bresman & Zellmer-Bruhn, 2013; Liu, Schuler, & Zhang, 2013; Luan et al., 2016). Moreover, despite these studies using different theories such as organizational structure theory, social cognition theory, and social identity theory, all of them have highlighted psychological safety as an important driver for engaging in external learning by team members. Though this line of inquiry concerning the motivational drivers is informative, it has failed to distinguish the different forms of external learning and omitted the factors associated with the opportunities that would enable or constrain an individual to engage in external learning. This omission is unfortunate because in many cases the absence of external learning is not the result of a lack of motivation among team members but rather that the individual is constrained by the limited opportunities embedded in his/her social structure for external learning (e.g., Phelps et al., 2012; van Wijk et al., 2008).

To better understand how social structural factors can promote or constrain an individual's opportunities to engage in task learning or contextual learning, I adopt social network theory to examine how and when task learning and contextual learning can be simultaneously fostered. A key tenet of social network theory is that the configurations of the social relationships that surround a node can enable and limit the node's opportunities to acquire, transfer, and create knowledge (e.g., Phelps et al., 2012). In prior social network literature, closure and brokerage are two main network configurations that have been highlighted as having substantial but different influences on individual knowledge seeking and learning behaviors (e.g., Burt, 1992; Coleman, 1988; Reagans & McEvily, 2003, 2008). Building upon this literature, Study 1 examines whether and how closure in the form of network density (i.e., the extent to which the alters in an ego's network are directly connected with each other) and brokerage operationalized as betweenness centrality (i.e., the extent to which an actor lies in the interaction paths connecting any two other unconnected members in a network) may respectively provide a focal individual with access to different forms of knowledge, thereby, promoting task learning and contextual learning.

Social network research also highlights the important role of individual attributes in realizing and mobilizing the resources available through network configurations (e.g., Baer, 2010; Reinholt et al., 2011). In particular, as activities for acquiring and transmitting knowledge from sources outside of the team boundary, the success of external learning is contingent upon the characteristics of the focal individual's knowledge structure (Reagans & McEvily, 2003). Knowledge depth (i.e., the degree to which an individual is knowledgeable about a specific domain) and knowledge breadth (i.e., the extent to which an individual's knowledge covers multiple domains) are two main characteristics of knowledge structure that I expect to exert substantial influence on the relationships between a social network and external learning (e.g., Dane, 2010; Haas & Ham, 2015). Specifically, knowledge depth enhances an individual's cognitive complexity in processing the knowledge in a focal knowledge domain, while knowledge breadth promotes an individual's cognitive flexibility in integrating knowledge from different domains. As such, I further propose that an individual employee's knowledge depth strengthens the positive association between network density and task learning, whereas an individual's knowledge breadth magnifies the positive relationship between betweenness centrality and contextual learning. The conceptual model in Study 1 is graphically depicted in Figure 2.

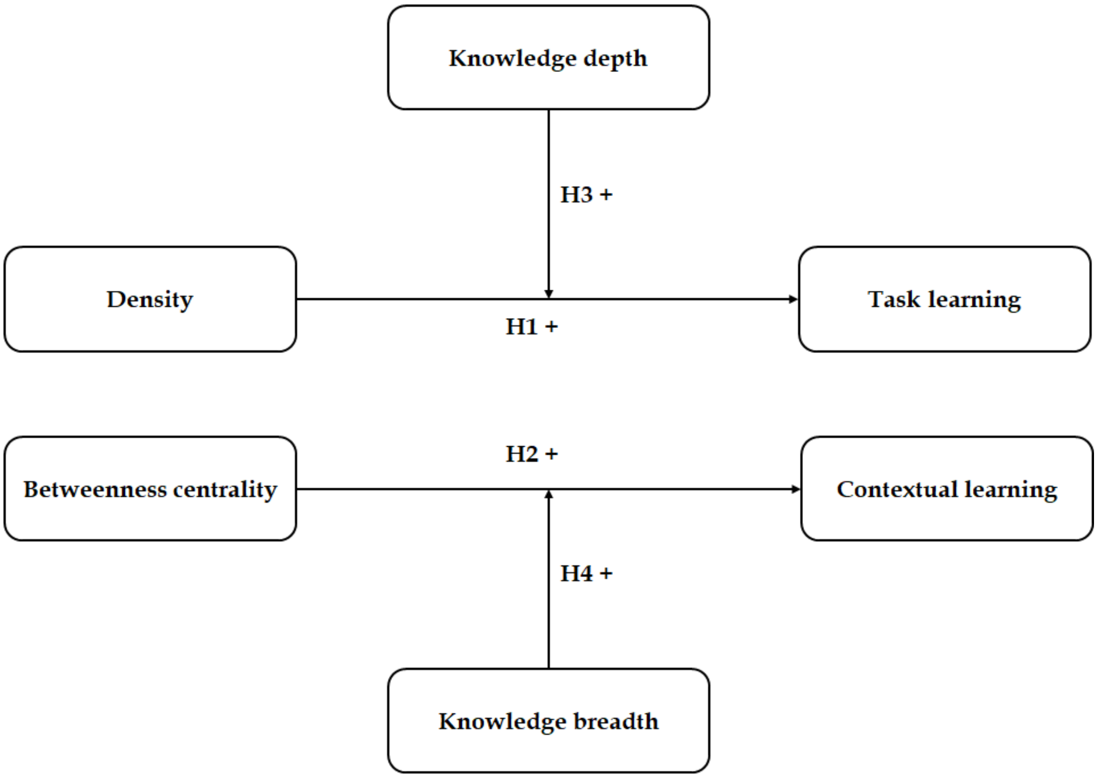

Figure 2. The conceptual model in Study 1

With a multiple-wave and multiple-source sample of 140 employees from a power company, I found support for the aforementioned hypotheses. In so doing, I contribute to the current literature in three ways. First, I account for how an individual may achieve different types of external learning from the social network perspective. Departing from the prior motivational approach for accounting for an individual's external learning activities (e.g., Bresman & Zellmer-Bruhn, 2013), my network-based model of external learning highlights the impact of social structures upon promoting an individual's external learning. Second, by testifying to the moderating role of knowledge depth and knowledge breadth in the network structure–external learning linkage, I identify the boundary conditions that influence the informational utilities of different network attributes for external learning.

Finally, the findings of this study advance the complementary perspectives of closure and brokerage by simultaneously examining both configurations while disentangling their effects on distinct forms of learning outcomes.

Theory and Hypotheses

A Social Network Theory of External Learning

The social network theory focuses on how the configurations of social relationships surrounding an individual enable or constrain an individual's opportunities to access, acquire, and transmit information and knowledge (e.g., Phelps et al., 2012). In prior social network literature, closure (cf. Coleman, 1988) and brokerage (cf. Burt, 1992) are two main network configurations highlighted as having substantial but different influences on individual knowledge seeking and learning behaviors (e.g., Reagans & McEvily, 2003, 2008).

On one hand, the perspective that advocates the benefits of closure suggests that density in an individual's personal network can help the individual to obtain consistent and reliable knowledge regarding how to complete a task (e.g., Morrison, 2002). These informational benefits arising from the external network provide the precondition for a team member to engage in task learning, which is focused upon learning from others outside the team with similar experiences of the key aspects of a team's task (Bresman, 2010; Harvey et al., 2018).

On the other hand, the perspective highlighting the utilities of brokerage suggests that betweenness centrality in an individual's personal network gives the individual access to nonredundant and diverse information regarding the organizational environment (e.g., Venkataramani, Richter, & Clarke, 2014). These informational benefits associated with the external network make it possible for a team member to engage in contextual learning, which emphasizes learning from external sources about key aspects of the context in which a team is operating (Bresman, 2010; Harvey et al., 2018).

Drawing on social network theory, in the following section I depict how density is positively associated with task learning while betweenness centrality is positively related to contextual learning.

External Network Density and Task Learning

Task learning focuses on obtaining similar experiences of key aspects of the team's task from others outside the team boundary (Bresman, 2013). As vividly described by Bresman (2013), the key procedures involved in task learning are "finding" and "copying." More specifically, in order to enact task learning, an individual first needs to locate who has the relevant experiences, and then approach the specific target to repeatedly probe and verify the details of the experiences (Bresman, 2013).

The social network theory of closure suggests that high levels of network density facilitate the flow and transfer of task-relevant knowledge. Network density essentially measures the number of redundant relationships in an ego's network (Shaw, Duffy, Johnson, & Lockhart, 2005). In this study, I focus on the connectedness among the alters who are external to an ego's team boundary. Studies on intergroup knowledge transfer have demonstrated that external ties are conduits of useful knowledge (Hansen, 1999; Wong, 2008). This is because employees external to the focal team usually have relevant knowledge and experience that cannot easily be generated by the internal members.

External network density is purported to promote task learning for two reasons. First, to the extent that alters in the external network frequently exchange information and knowledge about work and tasks, a shared understanding about each alter's expertise will form within the external network (e.g., Uzzi, 1997). This shared understanding can help an individual locate the best target to approach with regard to extracting relevant knowledge and experiences that can be applied to the team task in hand (e.g., Morrison, 2002). Second, the direct interaction between an individual and the alters in his/her external network provides many opportunities for questioning, clarifying, and understanding the task-relevant knowledge (e.g., Wong, 2008), thereby, promoting the focal individual's transfer of the relevant knowledge (e.g., Hansen, 1999). In sum, I propose the following hypothesis:

Hypothesis 1: The density of an individual's external network is positively related to task learning.

Betweenness Centrality and Contextual Learning

In contrast, contextual learning is referred to as activities that cross the team boundary to grasp the key aspects of the context in which a team is operating

(Harvey et al., 2018). To effectively enact such information scouting activities and form a systematic understanding of the environment outside of the team boundary, an individual is expected to have access to diverse and nonredundant sources of information (e.g., Ancona & Caldwell, 1992; Tushman & Scanlan, 1981). Betweenness centrality reflects the extent to which an individual lies in the interaction paths connecting any two unconnected alters in the network external to the focal team, thus, serving as a critical hub for the acquisition of diverse and unique information among these alters (Burt, Kilduff, & Tasselli, 2013).

I argue that a high degree of betweenness centrality promotes the opportunities for individual employees to engage in contextual learning. More specifically, an individual with high betweenness centrality within his/her external network is more likely to identify the opportunities and threats in the external environment from different sources (e.g., Burt, 2004). Additionally, the position of high betweenness centrality provides the focal individual with information about whether the current work in the team is aligned with the broader organizational needs (e.g., Venkataramani et al., 2014). Thus, I propose the following hypothesis:

Hypothesis 2: The betweenness centrality of an individual in his/her external network is positively related to contextual learning.

The Moderating Role of Knowledge Structure

Implicit in the aforementioned arguments is the notion that individuals with advantaged social configurations are able to fully utilize this advantage. Recent studies on social networks and knowledge management have emphasized that the likelihood of an individual leveraging information and knowledge in their social networks depends upon the individual's capacities to process different kinds of information (e.g., Anderson, 2008; Baer, 2010; Reinholt et al., 2011). These studies suggest that advantageous social networks offer potential access to resources, but the realization and propensity of leveraging such potential is contingent upon an individual's capacity to utilize those resources. Explicitly, as activities for acquiring and transmitting knowledge from sources outside of the team boundary, the success of external learning is contingent upon the characteristics of the focal individual's knowledge structure (e.g., Reagans & McEvily, 2003, 2008).

Knowledge depth and knowledge breadth are two main characteristics of knowledge structure that have been proposed in prior literature (e.g., Dane, 2010; Haas & Ham, 2015) and may have substantial influences on the relationships between social networks and external learning. Knowledge depth indicates the degree to which an individual is knowledgeable about a specific domain (e.g., Mannucci & Yong, 2018), which is beneficial for identifying and understanding key issues within a more specific work domain (e.g., Haas & Ham, 2015). In contrast to knowledge depth, which focuses on how in-depth one's knowledge in a specific domain is, knowledge breadth reflects the extent to which an individual's knowledge encompasses multiple domains (e.g., Mannucci & Yong, 2018), which is helpful for interpreting and integrating the diverse information arising from different domains (e.g., Mannor, Matta, Block, Steinbach, & Davis, 2017). Integrating the literature on the characteristics of knowledge structure with social network theory, I propose that knowledge depth will strengthen the effect of external network density on task learning, while knowledge breadth will magnify the effect of betweenness centrality on contextual learning.

Although a densely structured external network provides a context favorable to enacting direct interactions with alters for expertise acquisition, I argue that the informational utilities of density for task learning are more likely to be achieved when an individual's knowledge depth is high. Prior research has shown that individuals with high levels of knowledge depth in a particular domain tend to have better understandings of the key issues in work tasks and the associated interrelationships that exist between them (Dane, 2010; Fiske & Taylor, 2013). Such knowledge depth helps formulate a clear problem to investigate, thereby, facilitating the identification and location of the most appropriate target to approach within the available external network (e.g., Chi, Feltovich, & Glaser, 1981). Moreover, in-depth knowledge accessible via a dense network also leads to a more effective process of probing and clarifying the relevant questions during the direct interaction with the external knowledge sources (e.g., Kimball & Holyoak, 2000). Taken together, by enhancing the effectiveness of identifying and probing the most relevant knowledge in the dense external network, knowledge depth is expected to magnify the effects of external network density on task learning.

In contrast, an individual with a low level of knowledge depth is less likely to reap the benefits from the dense external network in support of task learning. As a result of an insufficient understanding of the knowledge in a specific domain, an individual with a low level of knowledge depth is unlikely to be able to identify what is lacking and needs to be learned from external knowledge sources, despite having a good understanding of every alter's expertise within the external network. As such, the focal individual is also unable to effectively locate the best target with the relevant expertise, or raise the most essential questions during the interaction with the external knowledge sources. In sum, I propose the following hypothesis:

Hypothesis 3: Knowledge depth moderates the positive relationship between external network density and task learning such that the relationship is more positive when knowledge depth is higher.

My aforementioned arguments suggest that occupying a position with high betweenness centrality in the external network offers an individual diverse and nonredundant information, thereby, providing rich opportunities for contextual learning. However, to fully recognize and utilize these opportunities, individual employees who occupy structurally advantageous positions are expected to possess high levels of knowledge breadth. More specifically, individuals with high levels of knowledge breadth have diverse knowledge across multiple domains, which facilitate the individuals' allocating attention to various stimuli in the external environment (e.g., Dane, 2010). By investing attention in different aspects of the external stimuli, individuals with structurally advantageous positions and a broad variety of knowledge are more likely to recognize the pertinent information concerning the opportunities and threats within the external environment (e.g., Grégoire, Barr, & Shepherd, 2010).

Moreover, possessing diverse knowledge across different domains equips the focal individuals with a greater capacity to comprehend the languages of different social worlds, which facilitates their integration of the different perspectives from various knowledge sources (Reagans & McEvily, 2008). Ultimately, the advantageous structural position coupled with diverse and nonredundant information amassed from different domains should enhance an individual's opportunity and propensity to engage in contextual learning. By promoting the capacity to recognize and integrate the diverse and nonredundant knowledge, knowledge breadth is expected to strengthen the effects of the betweenness centrality of an individual's external network upon contextual learning.

In contrast, an individual with a low level of knowledge breadth is less likely to leverage the position with high betweenness centrality in the external network for contextual learning. With a narrower scope of knowledge, individuals with low levels of knowledge breadth may find it challenging to comprehend and integrate the diverse information accessed from different social circles, leading to cognitive overload and the failure to identify the connections among the available information. Under such circumstances, individuals would be less likely to recognize the informational opportunities and threats concerning their external environment from their nonredundant social contacts. In sum, I propose the following hypothesis:

Hypothesis 4: Knowledge breadth moderates the positive relationship between betweenness centrality in the external network and contextual learning such that the relationship is more positive when knowledge breadth is higher.

Method

Sample and Procedure

To test the hypothetical relationships in the model, I collected data from a power company located in a city in southeastern China. The company produces and distributes electricity to the general public. In order to manage the complex technical and coordination demands they faced, the company had decentralized their organizational systems into seven relatively autonomous and independent work units. Within each unit, the employees had been further divided into several interconnected teams that undertook specialized, interdependent functions within the overall workflow (see Figure 3 for the organizational structure of the company). The teams within the same unit depended upon each other for critical resources such as materials, data, and information in order to accomplish their focal tasks and shared organizational-level objectives. In contrast, the teams from different units seldom interacted with each other since they were separated by the organization in order to function independently. As such, each team's success and effectiveness depended upon how well it integrated the diverse resources and information its members acquired from the interdependent teams within the same unit. In short, task learning and contextual learning were essential aspects of the team members' daily work.

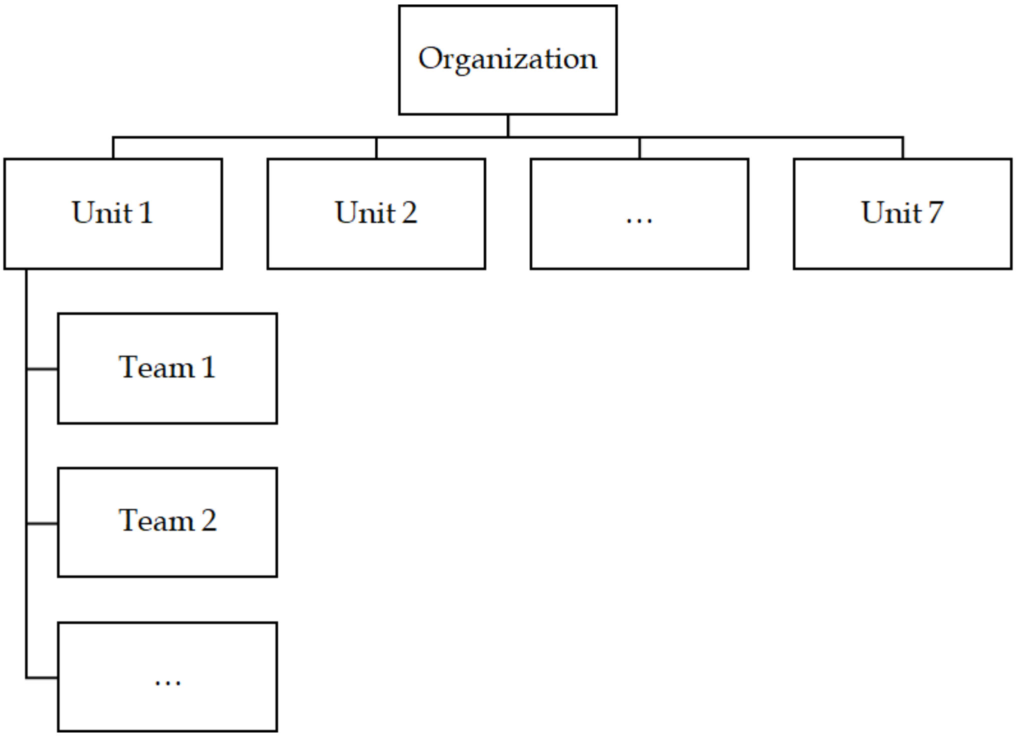

Figure 3. The organizational structure of the research context

I collected survey data at two time points separated by approximately two months (The data presented in this study were part of a broader data collection effort. Although the data used in Study 1 were also used in Study 2 of this dissertation, the variables used in these two studies do not overlap at all). At Time 1, the team members completed the questions related to advice network ties, and knowledge depth and breadth. At Time 2, the team leaders responded to questions about the frequency of each team member's task and contextual learning behaviors. I prepared the questionnaire by strictly following the translation-back-translation procedure recommended by Brislin (1980). In both waves, I administered the survey onsite, explained the purpose of the research, and promised to protect the confidentiality of the responses.

Among the 171 team members, 161 responded to the first-wave questionnaires in their entirety, with a response rate of 94%. Among the 43 team supervisors, 35 responded to the second-wave survey on their subordinates' external learning, resulting in a response rate of 81%. Considering that missing values will bias the estimates of social network configurations, I imputed the missing values when calculating the external network density and betweenness centrality by following the procedure suggested by Borgatti (2013). After matching the responses of the team members and team leaders, the final sample consisted of 140 members from 35 teams. Among the team members in the final sample, 100% were male, the mean age was 32 years (standard deviation = 6.6), and the majority had a degree of bachelor level or above (92%).

Measures

External network density and betweenness centrality (Time 1). The respondents were asked to indicate for each individual in their unit approximately how often they turned to the individual for information and knowledge in their daily work based on a five-point Likert scale (1 = never, 5 = very frequently). A table listing all the individuals in the same unit was provided to each respondent. A $n \times n$ matrix (n = total number of team members and leaders in a unit) was created, in which cell entry Xij represents the frequency at which individual i seeks information and knowledge from individual *j*. The data were then dichotomized such that an advice tie existed if the response was greater than the scale mid-point of 3.

External network density was measured by the ratio of the actual to the possible number of advice-seeking ties among alters in a focal individual's egocentric network (Borgatti, Everett, & Freeman, 2002). *Betweenness centrality in the external network* was measured by the extent to which a focal individual lay on paths linking two other unconnected alters in the egocentric network (Freeman, 1982; Marsden, 2002). Both of the network indexes were calculated with UCNET 6 (Borgatti et al., 2002).

Knowledge depth and breadth (Time 1). To measure knowledge depth and breadth, I first identified key knowledge domains in the research context. According to the interview with the managers before the data collection, I ascertained that there were nine functional domains in the daily operation of the organization, such as electrical engineering, ventilation management, fire control, and so on. To undertake a job in a functional domain, an employee needed to pass a technical assessment and obtain a professional certificate for the specific domain. The organization also encouraged employees to rotate within different functional domains. However, because of the high degree of difficulty in passing the technical assessments, few people had work experience across all nine functional domains. On average, employees had worked in four different functional domains.

Based on the information obtained from the interview, I listed the names of the functional domains in the questionnaire. After each of the functional domain names, I asked every team member to answer whether he had worked in the specific functional domain. If the answer was yes, I asked the team member to answer how many months he had worked in the specific functional domain. I also obtained information about each employee's current functional domain from the human resources managers. Based upon this information, I followed Mannucci and Yong (2018) and measured an individual's *knowledge depth* as the months that he had worked in the current functional domain. Consistent with de Vries et al. (2014), I calculated each individual's *knowledge breadth* by using Bunderson's (2003) version of Blau's (1977) heterogeneity index:

$$1 - \sum_{i=1}^{k} p_{i^2}$$

where p_i is the percentage of total months of work experience in the *i*th functional domain and *k* represents the total number of functional domains ($k = 9$ in the present study). This resulted in an overall score of an individual's knowledge breadth on a scale ranging from 0 (i.e., all work experience gathered in a single functional domain) to a theoretical maximum of .88 (i.e., total work experience evenly distributed across all nine domains).

Task learning (Time 2). I adopted the five-item scale developed by Bresman (2010) to measure task learning. Specifically, on a five-point Likert scale, I asked the team leaders to rate how often the team members had obtained similar task-relevant knowledge from others outside the team during the past month. Sample items were "*He goes out to gather information regarding who to contact for advice about how to complete the task*" and "*He talks to people outside the team about past failures to determine ways of improving the work process.*" The Cronbach's alpha for the scale was .96.

Contextual learning (Time 2). Consistent with Bresman (2010), I adopted five items from Ancona and Caldwell's (1992) scale of boundary spanning behaviors to measure contextual learning. Specifically, on a five-point Likert scale, I invited the team leaders to evaluate how frequently the team members had crossed the team boundary to obtain information about the external environment in which the team operated. Sample items were "*He scans the environment inside the organization for technical ideas/expertise*" and "*He finds out what competing teams are doing on similar projects.*" The Cronbach's alpha for the scale was .97.

Control variables. First, given that network size can affect an individual's opportunities to acquire and transfer knowledge from others outside of the team boundary, I controlled for this as the number of contacts in a focal individual's egocentric network. Second, I controlled for an individual's need for cognition since previous studies suggest this may influence people's ability to reap the benefits from the informational resources available within the social network (e.g., Baer, 2010). Third, because individuals with high proactive personalities may be better able to explore and exploit the resources provided by the social network (e.g., Lee, Qureshi, Konrad, & Bhardwaj, 2014), I also included proactive personality as a control variable.

Apart from these, I did not control for other demographic information for several reasons. First, I did not include gender and educational level as controls because 100% of the respondents were male and 92% of the respondents had a bachelor's degree or above. Second, I did not control for age and tenure because both of these factors were highly correlated with knowledge depth ($r \geq .75$). Considering that knowledge depth indicates the duration an individual has worked in a focal domain, these high correlations were reasonable. Actually, the results I report below remained stable when I included both age and tenure in the model; however, to avoid multicollinearity, I did not control for them.

Analytic Strategy

To test the hypothesized model, I conducted the analyses in two steps. I first conducted confirmatory factor analyses (CFAs) to confirm the discriminant validity of the measures. Next, I estimated the overall hypothetical model by using the path analysis technique. This technique enabled researchers to study the entire system of variables and obtain the estimates of all the hypothetical effects simultaneously, while controlling for the potential covariant effects that might have existed between the dependent variables (i.e., task learning and contextual learning). I performed both the CFAs and path analyses with *Mplus* 8.0 (Muthén & Muthén, 2017).

Results

Descriptive Statistics and Confirmatory Factor Analyses

Table 2 shows the means, standard deviations, and correlations of the variables in the hypothetical model. I conducted CFAs on two variables of the individual member's external learning, which were rated by their team leaders. The two-factor model had an acceptable fit (χ^2 = 84.72, *df* = 34, *RMSEA* = .10, *CFI* = .94, *TLI* = .93, *SRMR* = .03). Moreover, this model fitted the data better than an alternative model in which I treated the two variables as one factor (χ^2 = 228.01, *df* = 35, *RMSEA* = .20, *CFI* = .79, *TLI* = .73, *SRMR* = .07). Though the value of *RMSEA* was slightly larger than the traditional threshold (i.e., *RMSEA* ≤ .08), I think it was mainly because of the relatively small sample size (*N* = 140) in the model. Explicitly, according to Preacher and Coffman's (2006) computational simulation, given a power of 0.80 and α of 0.05, the sample size for the hypothetical model with a degree of freedom value of 34 to achieve *RMSEA* with 0.05 was approximately 305 observations. Moreover, Bentler and Chou (1987) suggested that the *RMSEA* tends to have a larger value with a smaller sample size while the *TLI* and *CFI* do not vary much with sample size. Therefore, I concluded that the above results provided legitimacy for the primary measurements and laid the foundations for the following analyses.

Table 2. Means, Standard Deviations, and Correlations

Variables	Mean	S.D.	1	2	3	4	5	6	7	8	9
1. Network size	18.85	9.40	—								
2. Need for cognition	5.58	.76	.15	(.85)							
3. Proactive personality	5.12	.81	.06	.56**	(.73)						
4. Density	63.75	2.17	-.47**	-.24**	-.18*	—					
5. Betweenness centrality	3.37	7.02	-.10	.12	.22*	-.44**	—				
6. Knowledge depth	35.75	46.48	-.43**	-.11	-.03	.26**	.07	—			
7. Knowledge breadth	.66	.22	.43**	.01	-.03	-.25**	-.01	-.40**	—		
8. Task learning	4.14	.81	.18*	-.02	.02	.05	-.08	-.28**	.29**	(.96)	
9. Contextual learning	4.32	.70	.27**	-.08	.01	.11	-.11	-.20*	.24**	.79**	(.97)

Note. N = 140. $^{*}p < .05$; $^{**}p < .01$.

The figures on the diagonal in parentheses are the alpha coefficients.

Hypotheses Testing

Hypothesis 1. The results in Table 3 indicated that density had significantly positive effects on task learning (b = .09, $p < .05$), but non-significantly positive effects on contextual learning (b = .07, *n.s.*). These results provided support for Hypothesis 1.

Hypothesis 2. As can be seen in Table 3, betweenness centrality had significantly positive effects on contextual learning (b = .06, $p < .01$), which supported Hypothesis 2. Though not hypothesized, betweenness centrality was also positively associated with task learning (b = .09, $p < .01$). I return to this finding in the discussion section.

Table 3. Unstandardized Coefficients of the Hypothetical Model

Predictors	Task learning		Contextual learning	
	Coeff.	*S.E.*	*Coeff.*	*S.E.*
Network size	.01	.04	.03	.04
Need for cognition	.07*	.03	.02	.02
Proactive personality	-.01	.02	-.01	.02
Density	.09*	.04	.07	.04
Betweenness centrality	.09**	.02	.06**	.01
Knowledge depth	-.03	.04	-.01	.04
Knowledge breadth	.03	.02	.03	.03
Density × Knowledge depth	.14**	.05	.05	.05
Betweenness centrality × Knowledge breadth	.08	.05	.11**	.03

Note. $N = 140$. * $p < .05$; ** $p < .01$.

Hypothesis 3. The results in Table 3 suggested that density and knowledge depth had a positive and significant interaction effect on task learning (b = .14, p < .01), but non-significantly positive effects on contextual learning (b = .05, *n.s.*). Moreover, I followed Cohen, Cohen, West, and Aiken's (2003) procedure to plot the interaction effect at two levels of knowledge depth (i.e., +1 SD and –1 SD) in Figure 4. A simple slopes test indicated that density was positively related to task learning at a higher level of knowledge depth ($\beta = .20, p < 0.01$), but was not significantly related to it at a lower level of knowledge depth (β = -*.03, n.s.*). Therefore, Hypothesis 3 was supported.

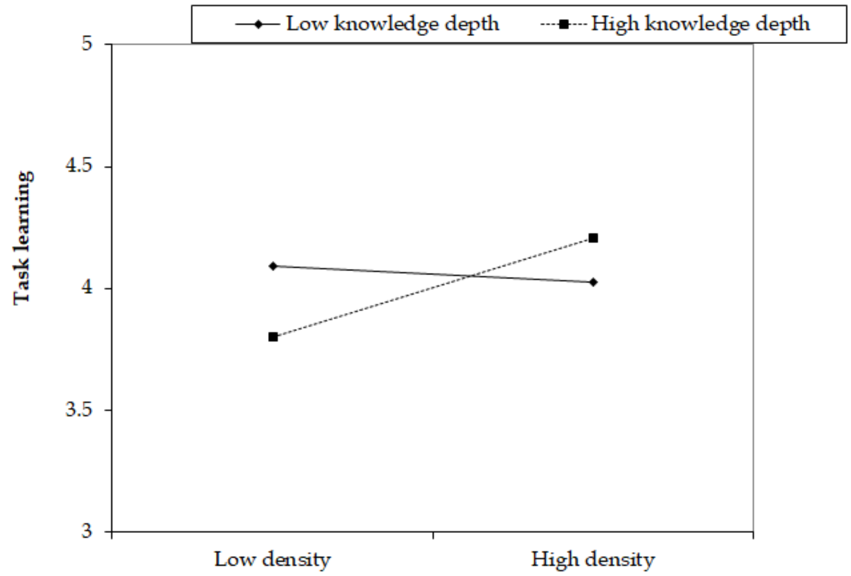

Figure 4. Interaction plot of density and knowledge depth in predicting task learning

Hypothesis 4. As can be seen in Table 3, betweenness centrality and knowledge breadth had a positive and significant interaction effect on contextual learning (b = .11, p < .01), but non-significant positive effects on task learning (b = .08, *n.s.*). Similarly, following Cohen et al. (2003), Figure 5 graphically displays this significant interaction effect at two levels of knowledge breadth (i.e., +1 SD and –1 SD). A simple slopes test indicated that betweenness centrality was positively related to contextual learning at a higher level of knowledge breadth (β = *.17, p < 0.01*), but was not significantly related to it at a lower level of knowledge breadth (β = *-.05, n.s.*). Thus, Hypothesis 4 was supported.

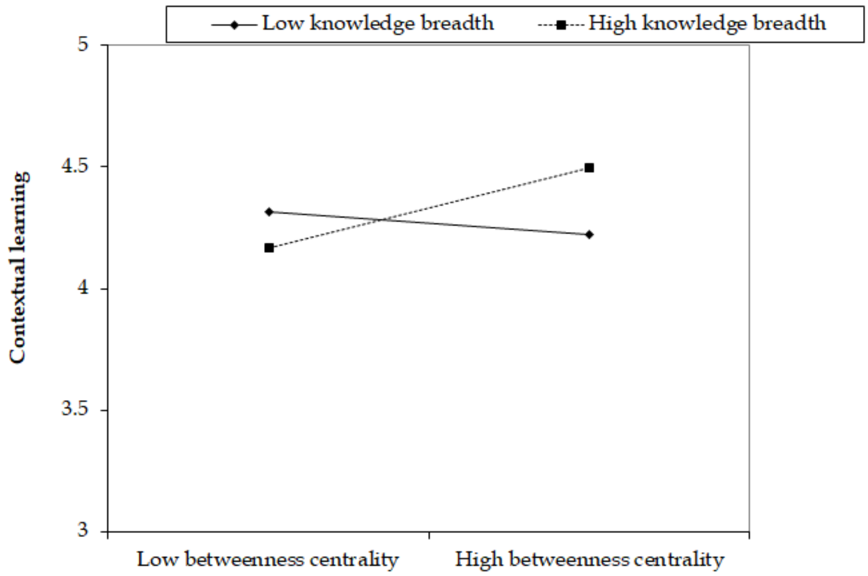

Figure 5. Interaction plot of betweenness centrality and knowledge breadth in predicting contextual learning

Discussion

Drawing upon social network theory, in this study, I attempted to investigate how and when the social network configurations of an individual could facilitate the individual's external learning. More specifically, I proposed and found that the density of an individual's external network was positively related to the individual's task learning, while the betweenness centrality of an individual in his external network was positively related to the individual's contextual learning. Additionally, I further identified the characteristics of the individuals' knowledge structures as the boundary conditions of the network configurations–external learning relationships. In particular, I proposed and found that an individual's knowledge depth strengthened the positive association between density and task learning. In contrast, an individual's knowledge breadth magnified the positive relationship between betweenness centrality and contextual learning.

In addition to the hypothetical relationships, I also found that betweenness centrality was positively related to task learning. Though this finding was unexpected, I think it was consistent with prior studies on brokerage and knowledge transfer (e.g., Reagans & McEvily, 2003, 2008). More specifically, Reagans and McEvily (2008) proposed that exposure to the diverse information associated with occupying a position of brokerage enabled an individual to better absorb, translate, and transfer knowledge from different sources. I speculated that the structurally induced capabilities could also be the underlying mechanism linking betweenness centrality and task learning, which emphasizes the transference of similar task experiences from others outside the team boundary. Taken together, this study has several implications for both theory and practice.

The implications of this study are threefold. First, by adopting social network theory, I identified external network density as the antecedent of task learning while betweenness centrality was the predictor of contextual learning. In so doing, I advance the theoretical underpinnings of the classification on external learning.

Second, this study joins an expanding body of literature that suggests that the realization of social network advantages is contingent upon individual characteristics (e.g., Anderson, 2008; Baer, 2010; Reinholt et al., 2011). In particular, I identify the characteristics of individuals' knowledge structures (i.e., knowledge depth and knowledge breadth) as new and important individual attributes. Third, I also advance the complementary perspectives of closure and brokerage. In contrast to prior studies that have treated closure and brokerage as two ends of a continuum, my findings reveal that density and betweenness centrality can facilitate different forms of external learning, both of which would contribute to team effectiveness.

Finally, task learning and contextual learning have been theorized as differing in terms of both their antecedents and consequences (e.g., Bresman, 2010). In this study I focused on density and betweenness centrality as the two different antecedents. I expect that the consequences resulting from task learning and contextual learning should also be different. Specifically, given that task learning emphasizes learning from other within-organization teams with similar experiences of key aspects of a team's task, I suggest it will lead to the members' utilization of task knowledge in the focal team. In contrast, contextual learning focuses on learning from external sources concerning key aspects of the within-organization context in which a team operates, which I expect to stimulate the reflexivity of the members' team work within the focal team. I theorize and test these expectations in the following two studies.

CHAPTER 4: STUDY 2

Management scholars have increasingly recognized the fact that teams can no longer rely solely upon themselves to generate all the knowledge necessary for the achievement of team objectives, but instead must engage in external learning (e.g., Argote et al., 2001; Edmondson et al., 2003). External learning, or "*interpersonal knowledge acquisition, sharing, and combination activities with individuals external to the group*" (Wong, 2004: 646), has been found to be positively related to team performance (e.g., Ancona & Bresman, 2006; Bresman, 2013; Peltokorpi & Hasu, 2015). Recent advances in this literature have suggested that team members may engage in various forms of external learning with distinct functions and obtain different knowledge accordingly (e.g., Bresman, 2010).

In this regard, Bresman and colleagues (Bresman, 2010, 2013; Harvey et al., 2018) have conceptualized and validated a two-dimensional model of external learning. The first type of external learning refers to *task learning*, which emphasizes learning from the organizational members who are external to the focal team and yet possess similar experiences of the key aspects of the tasks of the focal team. The second type is *contextual learning*, which consists of activities that emphasize learning from organizational members who are external to the focal team and have knowledge about the key aspects of the organizational context in which the focal team operates (Bresman, 2010; Harvey et al., 2018). Both forms of external learning acquire knowledge from outside the team and contribute to team performance, though in different ways.

In spite of the significant contributions made by this line of inquiry to bettering our understanding of how teams operate in complex and dynamic environments, it suffers from some limitations. More specifically, external learning behaviors are activities essentially undertaken by individual members on behalf of the team (Marrone, 2010), whereas the vast majority of research has conceptualized and operationalized the constructs at team level (e.g., Bresman & Zellmer-Bruhn, 2013; Liu et al., 2013; Luan et al., 2016; Wong, 2004). As a result, we know little about how the different knowledge obtained by the different external learning of individual team members is disseminated within teams and integrated into team-level performance. In addition, the notion that the two forms of external learning could facilitate team performance by importing necessary knowledge and resources is an implicitly held assumption that has seldom been investigated (e.g., Choi, 2002).

Moreover, the current literature contains the ill-advised assumption that the individual members engaging in external learning are able to diffuse the knowledge acquired from outside and exert the influence to make the teams adaptive to the external environment (Ancona & Caldwell, 2009; Tushman, 1977). Yet, knowledge recognition and utilization in teams are essentially dynamics that occur at the relational level (Bunderson, 2003). In other words, the same external learning behavior engaged in by different members may produce different attitudes and reactions in each member. More specifically, some qualitative studies suggest that team members who engage in external learning are not always appreciated and even regarded as black sheep by their teammates, which further harms team cohesiveness and performance (Ancona, 1990; Gibson & Dibble, 2013). In sum, this research evidence suggests a need for a deeper investigation of the microdynamics in dyads and a further exploration of the boundary conditions when studying the processes linking the external learning of individual members to team performance.

To extend the literature, I attempt to address research questions about how and when the different types of knowledge acquired by an individual team member's external learning are disseminated within teams and further integrated into team-level performance. I address these research questions by drawing upon the framework of team receptivity to the movement of personnel (Kane & Rink, 2017; Rink, Kane, Ellemers, & van der Vegt, 2013). The team receptivity framework is a relevant and useful theoretical perspective that has been adopted by previous studies in order to understand the processes and performance implications associated with personnel movement (e.g., external learning) in teams (e.g., Gruenfeld et al., 2000; Kane, Argote, & Levine, 2005; Rink et al., 2017). On top of this theoretical framework, I develop a multilevel conceptual model that is depicted in Figure 6. In the following two studies, I used two samples of time-lagged and multiple-source survey data to test the hypothetical model.

In completing the aforementioned, I make several contributions to the literature. First, by drawing upon the team receptivity framework and establishing a bottom-up model, I provide a theoretical account of how the knowledge acquired by an individual team member's external learning is disseminated and integrated into team-level performance. This advances the literature on external learning and boundary spanning by unfolding the previously assumed but seldom investigated mechanisms underlying the linkage between external activities and team effectiveness (Marrone, 2010). Second, on top of the team receptivity framework, I link different forms of external learning to distinct processes (i.e., task knowledge utilization vs. team work reflexivity), thereby, advancing the theoretical underpinnings of the taxonomy of task versus contextual learning (Bresman, 2010; Harvey et al., 2018). Third, the theorizing and findings associated with the moderating role of team performance pressure in Study 3 qualify the team receptivity framework as a useful theoretical perspective on one hand, while highlighting the distinctions between task and contextual learning on the other hand.

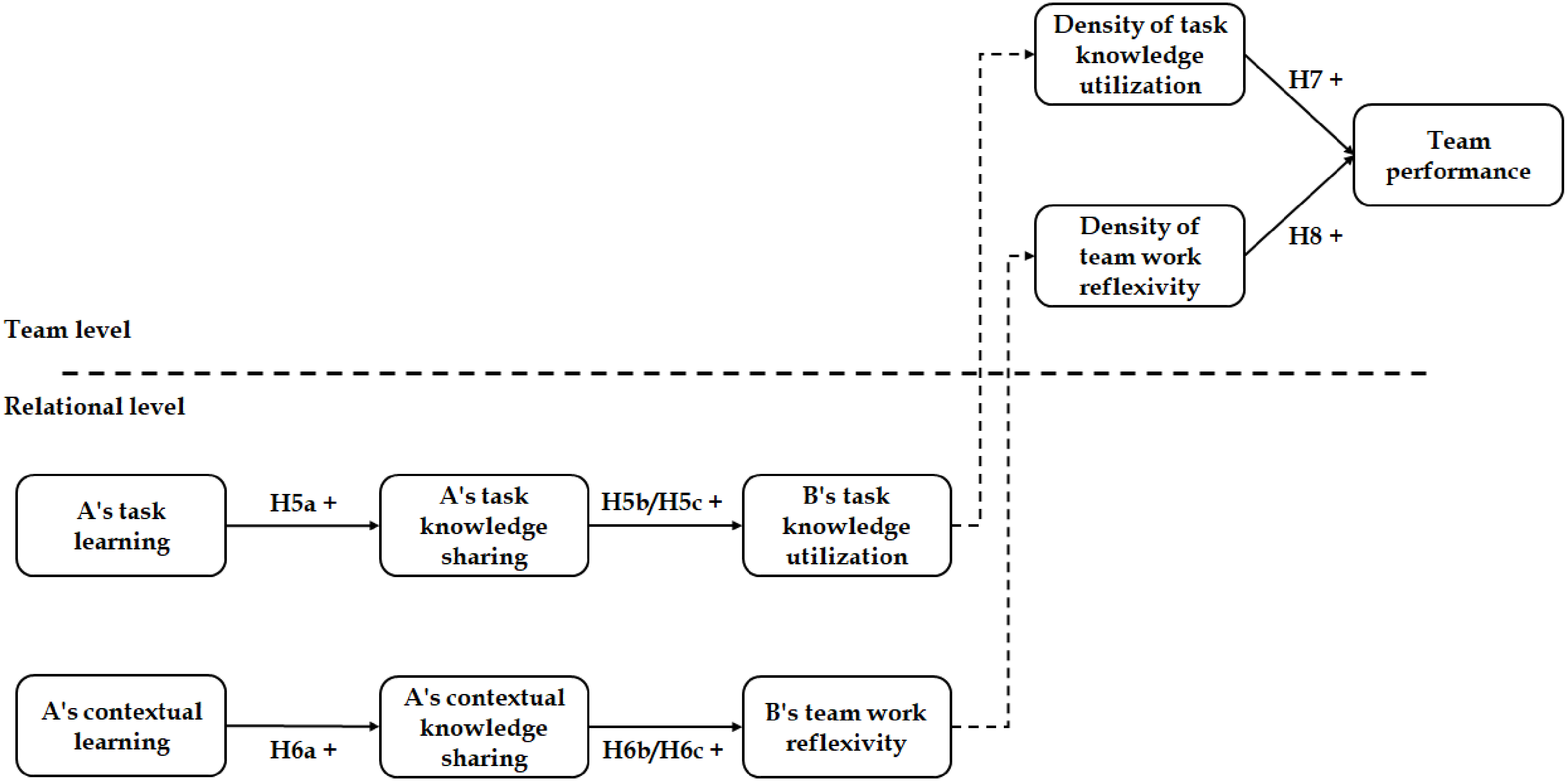

Figure 6. The conceptual model in Study 2

Theory and Hypotheses

Conceptualizing External Learning with the Team Receptivity Framework

To explicate how and when the different types of knowledge acquired by an individual team member are disseminated in teams and further integrated into team-level performance, I draw on the framework of team receptivity to personnel movement (Kane & Rink, 2017; Rink, et al., 2013). The team receptivity framework is a relevant and useful theoretical perspective that has been adopted by previous studies to understand the processes and performance implications associated with membership change and boundary spanning behaviors in teams (e.g., Gruenfeld et al., 2000; Kane et al., 2005; Rink et al., 2017). The key tenet of the team receptivity framework posits that a particular team member's movement across the team boundary (e.g., external learning) may lead another member in the same team to utilize the provided new knowledge and/or trigger another member to reflect upon the current work in the team. In this literature, these two processes are referred to as task knowledge utilization and team work reflexivity, respectively.

Drawing on the team receptivity framework (Kane & Rink, 2017; Rink, et al., 2013), in the following sections I explicate the interactions occurring in the dyads between Member A who engages in external learning and Member B who exhibits receptive reactions. In terms of the social relations model, Member A is referred to as a partner, while Member B is denoted as an actor (Kenny, 1994; Kenny, Kashy, & Cook, 2006). Specifically, I propose and detail that when a particular Member A engages in task learning and/or contextual learning, it will lead to Member B's task knowledge utilization and/or team work reflexivity, respectively.

In particular, although prior research has implicitly stated that the external learning of team members enhances team performance through the sharing of the knowledge obtained from the outside (e.g., Marrone, 2010; Peltokorpi & Hasu, 2015), we do not know whether the knowledge sharing processes do actually occur and whether there are conditions under which these processes are strengthened or weakened. To address this significant gap in the current literature, I also explicitly propose and test the processes of Member A's task/contextual knowledge sharing that underlies the linkages between Member A's task/contextual learning and Member B's task knowledge utilization and team work reflexivity, respectively. Moreover, on top of the team receptivity framework and associated empirical research (e.g., Konradt & Eckardt, 2016; Rink et al., 2017; Sung & Choi, 2012), I further argue that a higher level of task knowledge utilization and/or team work reflexivity among team members contributes to a better team performance.

Task Learning, Task Knowledge Sharing, and Task Knowledge Utilization

Task learning is referred to as activities that cross the team boundary in order to obtain similar experiences of the key aspects of the team's task from those outside the team boundary (Bresman, 2010). When Member A engages in task learning, s/he would usually first identify who outside the team boundary has the relevant expertise, and then s/he would attempt to extract the knowledge by observing others working on similar tasks or by inviting the experienced others to discuss ways to improve (e.g., Ancona & Bresman, 2006). By performing such task learning, Member A could obtain the knowledge about what needs to be done, how to do it, and what to avoid or omit when his/her own team undertakes similar tasks (e.g., Bresman, 2013). In addition, when working in teams, task orientation and collection orientation are always in the mind of the team member when s/he is undertaking the external learning on behalf of the team (Marrone, 2010). As such, I argue that when Member A obtains the knowledge of how to complete the similar tasks, s/he would share the task knowledge with her/his teammate, Member B. In support of my argument, previous studies have suggested that individuals situated at the interface of the team boundary and the external environment do transfer the new technique and knowledge from the outside into their teams (e.g., Perry-Smith & Mannucci, 2017; Tushman, 1977).

Drawing on the team receptivity framework (Kane & Rink, 2017; Rink, et al., 2013), I further argue that Member A's task knowledge sharing would lead to Member B's task knowledge utilization, which refers to Member B's inclination to utilize and adopt Member A's unique knowledge, skills, and aptitudes (Bunderson, 2003). This is because the task knowledge shared by Member A cannot be easily generated by the team and has the potential to help the team when they are performing similar tasks (Bresman, 2013). In particular, when Member B perceives that the task knowledge from Member A could help the team by standing on the shoulders of others who have trodden similar paths before and by avoiding reinventing the wheel and repeating the mistakes that others have experienced (Bresman, 2010), s/he will embrace the knowledge; and/or at least Member B will apply and recombine the knowledge shared by Member A when the team is performing the similar tasks. Consistent with my argument, previous studies have revealed that team members tend to adopt and utilize the task knowledge brought by a particular member across the team boundary (e.g., Kane, 2010; Kane et al., 2005). In sum, I propose the following hypotheses:

Hypothesis 5a: Member A's task learning is positively related to Member A's task knowledge sharing.

Hypothesis 5b: Member A's task knowledge sharing is positively related to Member B's task knowledge utilization.

Hypothesis 5c: Member A's task learning has a positively indirect relationship with Member B's task knowledge utilization through Member A's task knowledge sharing.

Contextual Learning, Contextual Knowledge Sharing, and Team Work Reflexivity

In contrast to task learning, contextual learning is defined as activities that cross the team boundary to grasp the key aspects of the context within which a team is operating (Bresman, 2010). When Member A engages in contextual learning, generally s/he scans the environment inside and outside the organization, scouts information regarding what the other teams are doing, probes the expectations and instructions from upper management, and collects ideas about technical and marketing trends (e.g., Ancona & Caldwell, 1992; Strobel, Tumasjan, Spoerrle, & Welpe, 2017). Through the execution of such contextual learning, Member A is able to acquire knowledge about the external environment within which his/her team operates as well as the associated opportunities and threats hidden in the background (e.g., Harvey et al., 2018; Pryor, Holmes, Webb, & Liguori, 2017). Similarly, with the task orientation and collection orientation always kept in mind (Marrone, 2010), I argue that when Member A obtains knowledge about the operational environment, s/he will share the contextual knowledge with her/his teammate, Member B. Lending indirect evidence for my argument, previous studies at team level have found that contacts engaging in cross-team communication are likely to share the environmental information gathered from the outside with teammates inside the team boundary (e.g., Gittell, 2002, 2000).

As suggested by the team receptivity framework, the information from the outside has stimulating properties which may trigger the team members' vigilance towards the external environment. As a result, team members may be forced into a new pattern of thinking and interacting (Kane & Rink, 2017; Rink et al., 2017). On top of the insights from this framework, I further argue that Member A's contextual knowledge sharing will lead to Member B's team work reflexivity, which entails Member B's tendency to reflect upon existing work processes and to adjust current working routines (West, 2000). More specifically, when confronted with the environmental information shared by Member A, it is very likely that Member B will engage in reflecting upon issues such as who the allies and competitors of the team are, what the expectations of upper management towards the team are, and whether the work of the team is aligned with the technical and marketing trends in the broader environment (e.g., Bresman, 2010; Liu et al., 2013). As a result, adaptations to the team work objectives and methods with regard to the external environment may be proposed and presented (e.g., Arrow & McGrath, 1993; Schippers, den Hartog, & Koopman, 2007). To sum up, I propose the following hypotheses:

Hypothesis 6a: Member A's contextual learning is positively related to Member A's contextual knowledge sharing.

Hypothesis 6b: Member A's contextual knowledge sharing is positively related to Member B's team work reflexivity.

Hypothesis 6c: Member A's contextual learning has a positively indirect relationship with Member B's team work reflexivity through Member A's contextual knowledge sharing.

Task Knowledge Utilization, Team Work Reflexivity, and Team Performance

Thus far, I have explicated how Member A's task learning and contextual learning will lead to Member B's task knowledge utilization and team work reflexivity at the relational level. However, my interest in explicating the interaction at the relational level is motivated by the assumption that the aggregated task knowledge utilization and team work reflexivity at team level are critical processes leading to high performances in teams whose effectiveness requires knowledge input by all the team members. Following previous studies linking lower within-team interactions to team-level properties (e.g., Liang, Shu, & Farh, 2019), I use the density of the task knowledge utilization and the density of the team work reflexivity in each team to describe the two corresponding aggregated team processes. Density refers to the ratio of actual connections to the total possible connections within a team, representing the amount or frequency of interactions among members within the team (Wasserman & Faust, 1994). In teams with a high density of task knowledge utilization, each member of the team utilizes and is utilized by every other member in terms of the task-related knowledge. Similarly, in teams with a high density of team work reflexivity, each member of the team stimulates and is stimulated by every other member in terms of reflexivity on the team work. In the following, I explicate why a team performs better when it has a higher density of either task knowledge utilization or team work reflexivity.

In particular, there are two reasons for teams with higher density task knowledge utilization to experience higher team performances. First, as suggested by the aforementioned discussion, the knowledge acquired by task learning may help team members better understand and evaluate the consequences of each specific action and approach to tasks, thereby, avoiding costly errors and search efforts (e.g., Bresman, 2010, 2013). As such, when each member of a team considers and is considered by every other member in terms of the task knowledge obtained from diverse sources from outside of the team boundary, the team will have a greater pool of knowledge that can be accessed and channeled (e.g., van Knippenberg, 2017), which should in turn contribute to the more effective execution and achievement of the team objectives (e.g., Gino, Argote, Miron-Spektor, & Todorova, 2010).

Second, the presence of a substantial stock of knowledge also offers the teams many opportunities to engage in higher-order information processing (e.g., van Knippenberg, de Dreu, & Homan, 2004). Team members may deliberately exploit and integrate the available knowledge to generate new routines and procedures for the local tasks in their teams (e.g., Faraj & Sproull, 2000). In support of my arguments, the research on the utilization of expertise has suggested that teams perform better when the knowledge and expertise of every member is recognized and leveraged (e.g., Reagans, Miron-Spektor, & Argote, 2016; Sherf, Sinha, Tangirala, & Awasty, 2018; Sung & Choi, 2012). Therefore, I propose the following hypothesis:

Hypothesis 7: The density of task knowledge utilization among team members is positively related to team performance.

In a similar vein, I argue that teams with a higher density of team work reflexivity will have a higher team performance. According to Bresman and colleagues (Bresman, 2010; Harvey et al., 2018), the knowledge acquired by contextual learning is useful for team members in order to keep track of the external environment in which the team operates as well as the associated opportunities and threats hidden in the background. Accordingly, when each member of a team stimulates and is stimulated by every other member to reflect on team work objectives and methods through exchanging contextual knowledge, the number and scope of issues involved in the reflexivity should be much enlarged (e.g., Schippers, den Hartog, Koopman, & Wienk, 2003; Shin, 2014). As such, the team should have diverse and in-depth perspectives concerning what was effective and what was ineffective in prior working experiences (e.g., Schippers, den Hartog, Koopman, & van Knippenberg, 2008). Consequently, team members should be able to form a more systematic and comprehensive understanding of past successes and failures (e.g., Ellis, Carette, Anseel, & Lievens, 2014).

Furthermore, based on this systematic and comprehensive understanding, team members can produce better ideas about how to adapt those aspects of the team’s objectives and methods that are not aligned with the external environment (e.g., Schippers, Edmondson, & West, 2014). In this way, the team are able to remain abreast of the broader external environment, thereby, enhancing the team performance (e.g., Schippers et al., 2007). Consistent with my arguments, qualitative and quantitative reviews have confirmed that a positive relationship between team work reflexivity and team performance generally exists across field and experimental studies (Konradt, Otte, Schippers, & Steenfatt, 2016; Tannenbaum & Cerasoli, 2013). Therefore, I propose the following hypothesis:

Hypothesis 8: The density of team work reflexivity among team members is positively related to team performance.

Method

Sample and Procedure

Work teams in a power company located in a city in eastern China agreed to participate in my study. The company generates and distributes electricity to the general public. To manage the complex technical and coordination demands they faced, the company had decentralized their organizational systems into relatively autonomous, interdependent teams that undertook specialized, interdependent functions in the overall workflow. The teams depended on each other for critical resources such as materials, data, and information in order to accomplish their focal tasks and shared organizational-level objectives. As such, each team's success and effectiveness depended upon how well it integrated the diverse resources and information its members acquired from interdependent entities. In short, external learning and internal knowledge integration were essential parts of the team members' daily work. Therefore, this sample was suitable for testing the hypothetical model.

I collected the survey data at two time points separated by approximately one month (The data presented in this study were part of a broader data collection effort.

Although the data used in Study 2 were also used in Study 1 of this dissertation, the variables used in these two studies do not overlap at all). Before the data collection, I obtained a roster with 171 team members nested in 43 teams. At Time 1, every team member answered questions regarding the task and contextual learning activities engaged in by each of his teammates. In assessing task and contextual learning, I utilized the round-robin method (Kenny, 1994). That is, each member of a team rated and was rated by every other member in terms of the frequency of their task and contextual learning behaviors. Approximately one month later (Time 2), by adopting the same round-robin approach, I asked every team member to answer questions regarding the task and contextual knowledge sharing of each peer as well as his own task knowledge utilization and team work reflexivity activities when interacting with each peer in the same team. At the same time, I also required the team leaders to evaluate the performance of the team they supervised.

Among the 171 team members, 136 completed the multi-wave questionnaires, with a response rate of 80%. Because missing values may bias the estimates of the dyadic interaction within teams (Kenny et al., 2006), I followed the procedure suggested by Schönbrodt, Back and Schmukle (2012) and imputed the missing values based on the responses from the non-responding member's teammates. However, in six teams, no more than one member had answered the multi-wave questionnaires completely, which made the missing imputation impossible. Therefore, I excluded these six teams (12 individual members) from the final sample. As a result, the final sample consisted of 633 dyads among 159 members in 37 teams. In the final sample, 100% were male, the mean age was 30.41 years (standard deviation = 4.96), and the majority had a bachelor's degree (96%).

Measures

I adopted well-established scales to measure the constructs in the hypothetical model. And most of the variables at the relational level were measured with the round-robin approach, which required every team member to evaluate every other team member on the same items. To avoid causing the cognitive overload of the participants, I adapted the measures of some variables at relational level to ensure that each of them was measured with no more than three items. Given that the original measurements were developed in English while the survey was administered in Chinese, I followed Brislin's (1980) translation-back-translation procedure to set up the questionnaire. Specifically, I translated the English scales into Chinese first. Then, two doctoral students in management with bilingual expertise reviewed the questionnaire items to ensure semantic clarity. Unless otherwise stated, the team members responded to the measurement items on five-point Likert scales ranging from 1 (totally disagree/never) to 5 (totally agree/always).

Task learning (Time 1). I adopted three items from the scale developed by Bresman (2010) to measure task learning. Specifically, on a five-point Likert scale, I asked team members to rate how frequently each peer in the team had obtained similar task-relevant knowledge from others outside the team during the past month.

A sample item was "*[X] talks to people outside the team about past failures to determine ways of improving the work process.*" The Cronbach's alpha for the scale was .96.

Contextual learning (Time 1). Consistent with Bresman (2010), I adopted three items from Ancona and Caldwell's (1992) scale of boundary spanning behaviors to measure contextual learning. Specifically, on a five-point Likert scale, I invited team members to evaluate how often each peer in the team had crossed the team boundary to obtain information concerning the external environment in which the team operates. A sample item was "*[X] scans the environment beyond the team boundary for information on opportunities and threats.*" The Cronbach's alpha for the scale was .96.

Task knowledge sharing and contextual knowledge sharing (Time 2). To measure the two types of knowledge sharing, I replaced the verbs related to "learning" with verbs related to "sharing" in each item for measuring task and contextual learning. Specifically, on a five-point Likert scale, I invited every team member to evaluate how often each peer in the team had shared task and contextual knowledge with him during the past month. Sample items were "*[X] shares with me other teams' past failures and experiences that he obtained by discussing with others outside the team* (task knowledge sharing)" and "*[X] shares with me information on opportunities and threats that he obtained by scanning the environment beyond the* *team boundary* (contextual knowledge sharing).” The Cronbach’s alpha for the two scales were .97 and .97, respectively.

Task knowledge utilization (Time 2). I adopted three items from the scale developed by Rink and Ellemers (2015) to measure task knowledge utilization. Specifically, on a five-point Likert scale, I asked every team member to rate how frequently he had utilized the knowledge and suggestions provided by each peer in the team during the past month. A sample item was “*I accept a better work approach from [X]*.” The Cronbach’s alpha for the scale was .97.

Team work reflexivity (Time 2). To measure team work reflexivity, I adopted three items from the scale originally developed by Swift and West (1998). Specifically, on a five-point Likert scale, I asked every team member to rate how frequently he had engaged in reflection and adaptation when interacting with each peer in the team during the past month. A sample item was “*I review the work objectives and methods when interacting with [X]*.” The Cronbach’s alpha for the scale was .94.

Density of task knowledge utilization and density of team work reflexivity (Time 2). Given that knowledge utilization and team work reflexivity were measured with the round-robin method, the network among the team members on these two variables was definitely captured. Based on this matrix data, I measured the density of each variable by calculating the ratio of the actual to the possible number of connections among the team members in terms of task knowledge utilization and team work reflexivity.

Team performance (Time 2). I used the three-item scale developed by de Jong and Elfring (2010) to measure team performance. More specifically, I required team leaders to grade the performances of their teams in the light of established performance standards on a seven-point Likert scale. The three items were "*The amount of work the team produces,*" "*The quality of work the team produces,*" and "*Your overall evaluation of the team's effectiveness.*" The Cronbach's alpha for this scale was .91.

Control variables. To minimize alternative explanations and establish the incremental predictive validity of the independent variables (e.g., A's task and contextual learning), I controlled for several variables at different levels. First, at an individual level, I followed prior knowledge management research to control for Member A and B's demographic information, including age and educational level (e.g., Wang & Noe, 2010). Prior studies have suggested that individuals of younger ages and higher educational levels may be more likely to engage in knowledge exchange processes (e.g., Kim, Kim, & Yun, 2015; Nerstad et al., 2018). However, I did not include gender as a control because 100% of the respondents were male.

Second, at the relational level, I followed previous studies on interpersonal interactions and controlled for the dyadic tenure between A and B as well as A's higher status than B (e.g., Liu et al., 2015). A dyad with longer tenure may indicate a stronger relationship between A and B, which may further influence the knowledge transfer processes (e.g., Hansen, 1999; Levin & Cross, 2004). I measured the dyadic tenure by asking every team member to report how long he had worked with each peer in the team. Moreover, the status differences between A and B may also influence the interpersonal dynamics and knowledge exchange (e.g., Blader, Shirako, & Chen, 2016; Bunderson, 2003). Therefore, I followed Liu et al.'s (2015) three-step approach to operationalize and control for A's higher status than B. Specifically, I first asked every team member to rate each peer's social status in the team with Anderson, John, Keltner, and Kring's (2001) three-item scale. Following this, I averaged the status ratings assigned to a particular team member by all the other teammates to derive each member's social status score. Lastly, by comparing the status scores of A and B in each dyad, I could assign a value of 1 if A had higher status, a value of -1 if B had higher status, and a value of 0 if A and B had equal status.

Third, at team level, I also controlled for three factors that might determine the necessities and influences of A's external learning on knowledge sharing processes. In particular, task learning focuses upon obtaining similar experiences about the key aspects of tasks from others outside of the team boundary (Bresman, 2010). As such, it is more useful and influential for members in a team that has high levels of task similarity with other external teams to engage in task learning and sharing (e.g., Simonin, 1999). Therefore, I controlled for external task similarity by asking team members to report the extent to which the tasks in the focal team were similar to other external teams on a seven-point Likert scale. Moreover, contextual learning focuses upon acquiring information about the key aspects of the organizational context in which the focal team operates (Bresman, 2010). Accordingly, it is more necessary and helpful for members in a team that has high levels of interdependence on other external teams to engage in contextual learning and sharing (e.g., Choi, 2002; Drach-Zahavy & Somech, 2010; Joshi et al., 2009). As such, I required team members to indicate the perceived external interdependence with de Vries et al.'s (2014) three items on a seven-point Likert scale and included it as a control variable. Finally, as previous studies have shown that team members' shared goals can promote knowledge exchange and utilization activities (e.g., de Dreu, 2007; Kane, 2010; Kane et al., 2005), I controlled for this by asking team members to report the shared goals of members in the same team using Lam, van der Vegt, Walter, and Huang's (2011) three-item scale on a seven-point Likert scale.

Analytical Strategy

I first conducted CFAs to confirm the discriminant validity of the measures. Next, I decomposed variances of the outcome variable at relational level (i.e., task knowledge sharing, contextual knowledge sharing, task knowledge utilization, team work reflexivity) to confirm that social relations models would be appropriate to use to analyze the data. Then, I ran social relations modeling analyses to test the hypotheses at the relational level. To further confirm hypotheses regarding mediation effects, I also adopted the parameter-based bootstrapping approach to estimate the 95% confidence intervals of the effects (Preacher & Selig, 2012). Moreover, I also implemented hierarchical regression analyses to test the hypothetical relationships at team level. The CFAs were performed with *Mplus* 8.0 (Muthén & Muthén, 2017), the hypotheses at relational level were analyzed with R package *pdSRM* (Knight & Humphrey, 2019), and the hypotheses at team level were examined with linear regression models in SPSS.

Results

Descriptive Statistics and Confirmatory Factor Analyses

Given that I would test the hypothetical relationships at relational and team levels separately, I present the means, standard deviations, and correlations of the variables at each level, respectively. Table 4 shows the descriptive statistics at relational level while Table 5 displays the descriptive statistics at team level.

Table 4. Means, Standard Deviation and Correlates among Variables at Relational Level

Variables	Mean	SD	1	2	3	4	5	6	7	8	9	10	11	12	13
1. B's age	29.69	3.85	—												
2. B's education	2.99	.20	-.26	—											
3. A's age	29.69	3.85	.31	-.24	—										
4. A's education	2.99	.20	-.24	.56	-.26	—									
5. Dyadic tenure between A and B	12.84	19.71	.17	-.03	.23	-.01	—								
6. A's higher status than B	.00	.93	-.22	-.05	.21	.05	.12	(.94)							
7. Team size	5.79	1.79	-.07	.16	-.07	.16	-.10	.00	—						
8. External task similarity	5.70	.51	-.01	.03	-.01	.03	.13	.00	.15	—					
9. External interdependence	6.16	.56	.12	.00	.12	.00	.02	.00	.11	.43	(.95)				
10. Team shared goal	6.47	.55	.06	-.07	.06	-.07	-.06	.00	.24	.34	.68	(.99)			
11. A's task learning	4.21	.85	.00	-.05	.10	.01	.09	.36	.05	.11	.39	.32	(.96)		
12. A's contextual learning	4.50	.73	-.01	-.11	.12	-.01	.02	.27	.02	.05	.43	.37	.79	(.96)	
13. A's task knowledge sharing	4.18	.83	-.05	-.04	.03	-.05	.08	.24	-.07	.13	.28	.34	.63	.58	(.97)
14. A's contextual knowledge sharing	4.18	.82	-.09	.00	.04	-.04	.09	.21	-.10	.17	.27	.27	.59	.58	.88
15. B's task knowledge utilization	4.13	.82	-.10	-.01	.01	-.02	.06	.24	-.01	.17	.25	.25	.58	.53	.85
16. B's team work reflexivity	4.14	.83	-.13	.00	-.01	-.03	.06	.19	-.02	.19	.25	.23	.55	.53	.81

Note. N = 633 dyads with 159 members of 37 teams. Variables at individual and team levels were assigned to relational level.

Correlations no less than |.09| are significant at p < .05, and correlations no less than |.10| are significant at p < .01.

Table 4 Means, Standard Deviation and Correlates among Variables at Relational Level (continued)

Variables	**14**	**15**	**16**
14. A’s contextual knowledge sharing	(.97)		
15. B’s task knowledge utilization	.84	(.97)	
16. B’s team work reflexivity	.88	.90	(.94)

Note. N = 633 dyads with 159 members of 37 teams. Variables at individual and team levels were assigned to relational level.

Correlations no less than |.09| are significant at p < .05, and correlations no less than |.10| are significant at p < .01.

Table 5. Means, Standard Deviation and Correlates among Variables at Team Level

Variables	Mean	SD	1	2	3	4	5	6	7
1. Team size	4.30	1.75	—						
2. External task similarity	5.69	.54	-.03	—					
3. External interdependence	6.21	.52	-.15	.36*	(.95)				
4. Team shared goal	6.48	.53	-.11	.46**	.60**	(.99)			
5. Density of task knowledge utilization	4.16	.45	-.10	.25	.35*	.35*	—		
6. Density of team work reflexivity	4.15	.46	-.02	.23	.37*	.35*	.91**	—	
7. Team performance	6.47	.51	-.07	.11	-.13	.05	.01	.13	(.91)

Note. N = 37. * *$p < 0.05$;* ** *$p < 0.01$.*

The figures on the diagonal in parentheses are the alpha coefficients.

I conducted CFAs on the seven variables rated by the team members with the round-robin design (i.e., status, task learning, contextual learning, task knowledge sharing, contextual knowledge sharing, task knowledge utilization, team work reflexivity). The seven-factor model had an acceptable fit ($\chi^2/df = 3.70$, $p < .01$, $RMSEA = .07$, $CFI = .98$, $TLI = .97$, $SRMR = .02$). This model fit the data better than alternative models when the following variables were combined: (1) task learning and contextual learning ($\Delta\chi^2/\Delta df = 155.37$, $p < 0.01$); (2) task knowledge sharing and contextual knowledge sharing ($\Delta\chi^2/\Delta df = 114.78$, $p < 0.01$); (3) task knowledge utilization and team work reflexivity ($\Delta\chi^2/\Delta df = 73.31$, $p < 0.01$); (4) the aforementioned three pairs of constructs, respectively ($\Delta\chi^2/\Delta df = 129.84$, $p < 0.01$); (5) the variables measured at Time 1 and the variables measured at Time 2, respectively ($\Delta\chi^2/\Delta df = 156.80$, $p < 0.01$); and (6) all of the variables ($\Delta\chi^2/\Delta df = 324.70$, $p < 0.01$). These results show that the measures captured distinct constructs.

Variance Decomposition

Prior to testing the hypotheses, I first used null models to decompose the variances in task knowledge sharing, contextual knowledge sharing, task knowledge utilization and team work reflexivity into team, actor (B), partner (A), and dyad components. Table 6 presents the results of this variance decomposition. The dyad-level component, which is a combination of systematic dyadic variation and residual, was sizable for task knowledge sharing (17%), contextual knowledge sharing (14%), task knowledge utilization (23%), and team work reflexivity (16%).

In line with prior research, individual-level dynamics also contributed to variances in task knowledge sharing (actor [B] = 64%, partner [A] = 3%), contextual knowledge sharing (actor [B] = 70%, partner [A] = 1%), task knowledge utilization (actor [B] = 61%, partner [A] = 3%), and team work reflexivity (actor [B] = 70%, partner [A] = 2%). Consistent with previous studies on the team-level antecedents of individual-level knowledge sharing processes, team level components also influenced variances in task knowledge sharing (15%), contextual knowledge sharing (15%), task knowledge utilization (13%), and team work reflexivity (12%). The results of the variance decomposition show the necessity of analyzing the data with the social relations model.

Table 6. Results of Social Relations Model Variance Decomposition

Sources	A's task knowledge sharing		A's contextual knowledge sharing		B's task knowledge utilization		B's team work reflexivity	
	Variances	*Percentages (%)*	*Variances*	*Percentages (%)*	*Variances*	*Percentages (%)*	*Variances*	*Percentages (%)*
Group	0.10	15	0.09	15	0.08	13	0.08	12
Actor	0.42	64	0.43	70	0.40	61	0.46	70
Partner	0.02	3	0.01	1	0.02	3	0.01	2
Dyad	0.11	17	0.09	14	0.15	23	0.11	16

Note. N = 633 dyads with 159 members of 37 teams.

Hypotheses Testing

Hypothesis 5a. In support of Hypothesis 5a, Model 3 in Table 7 indicated that Member A's task learning was significantly and positively related to Member A's task knowledge sharing (b = .27, p < .01), even if Member A's contextual learning was simultaneously included.

Table 7. Results of SRM Predicting A's Task Knowledge Sharing

Variables	**A's task knowledge sharing**		
	M1	**M2**	**M3**
Control variables			
B's age	.00	.00	.00
B's education	.00	.01	.05
A's age	-.00	-.00	-.00
A's education	-.16	-.13	-.15
Dyadic tenure between A and B	.00	.00	.00
A's higher status than B	.13**	.08**	.07**
Team size	-.03	-.04	-.03
External task similarity	-.07	-.02	-.00
External interdependence	.25	.06	.02
Team shared goal	.32	.29*	.28*
Main effects			
A's task learning		.33**	.27**
A's contextual learning			.14*
Pseudo R^2	.15	.36	.38
Δ Pseudo R^2		.21	.02

Note. N = 633 dyads with 159 members of 37 teams. $^{*}p < .05$, $^{**}p < .01$.

Hypothesis 5b. As can been seen in Model 3 in Table 8, Member A's task knowledge sharing was significantly and positively related to Member B's task knowledge utilization (b = .56, p < .01), even if Member A's contextual knowledge sharing was simultaneously included. Therefore, Hypothesis 5b was supported.

Table 8. Results of SRM Predicting B's Task Knowledge Utilization

Variables	**B's task knowledge utilization**				
	M1	**M2**	**M3**	**M4**	**M5**
Control variables					
B's age	-.01	-.02	-.01	-.02*	-.01
B's education	-.07	-.05	-.07	-.05	-.08
A's age	-.00	.00	-.00	.00	-.00
A's education	-.09	.03	.04	.03	.04
Dyadic tenure between A and B	.00	.00	.00	.00	.00
A's higher status than B	.12**	.02	.02	.01	.01
Team size	-.01	.01	.02	.01	.02
External task similarity	.08	.13	.11	.13	.11
External interdependence	.24	.03	.02	.00	.00
Team shared goal	.15	-.10	-.10	-.10	-.10
Main effects and mediation effects					
A's task learning				.08**	.05
A's contextual learning					-.02
A's task knowledge sharing		.79**	.56**	.76**	.55**
A's contextual knowledge sharing			.34**		.33**
Pseudo R^2	.09	.69	.72	.70	.72
Δ Pseudo R^2		.60	.03	.01	.02

Note. N = 633 dyads with 159 members of 37 teams. $^{*}p < .05$, $^{**}p < .01$.

Hypothesis 5c. The results of Model 5 in Table 8 suggested that the effect of Member A's task knowledge sharing on Member B's task knowledge utilization was positive and significant (b = .55, p < .01), while the effect of Member A's task learning on Member B's task knowledge utilization was positive but not significant (b = .05, *n.s.*). These results provided some preliminary support for the hypothesis. To further confirm the mediation effect, I calculated the indirect effect of Member A's task learning on Member B's task knowledge utilization through Member A's task knowledge sharing and estimated its 95% confidence interval with 20,000 parameter-based bootstrapping (Preacher & Selig, 2012). The results indicated that the indirect effect was positive and had a 95% CI excluding zero (indirect effect = .148; 95% CI: [.096, .203]). These results provided support for Hypothesis 5c.

Hypothesis 6a. In support of Hypothesis 6a, Model 3 in Table 9 indicated that Member A's contextual learning was significantly and positively related to Member A's contextual knowledge sharing (b = .16, p < .01), even if Member A's task learning was simultaneously included.

Table 9. Results of SRM Predicting A's Contextual Knowledge Sharing

Variables	**A's contextual knowledge sharing**		
	M1	**M2**	**M3**
Control variables			
B's age	-.01	-.01	-.01
B's education	.06	.05	.10
A's age	.00	.00	.00
A's education	-.12	-.09	-.11
Dyadic tenure between A and B	.00	.00	.00
A's higher status than B	.07**	.03	.03
Team size	-.05	-.05	-.05
External task similarity	.02	.06	.08
External interdependence	.21	.06	.02
Team shared goal	.22	.20	.19
Main effects			
A's task learning		.27**	.20**
A's contextual learning			.16**
Pseudo R^2	.09	.28	.32
Δ Pseudo R^2		.19	.04

Note. N = 633 dyads with 159 members of 37 teams. $^{*}p < .05$, $^{**}p < .01$.

Hypothesis 6b. As can been seen in Model 3 in Table 10, Member A's contextual knowledge sharing was significantly and positively related to Member B's team work reflexivity (b = .65, p < .01), even if Member A's task knowledge sharing was simultaneously included. Therefore, Hypothesis 6b was supported.

Table 10. Results of SRM Predicting B's Team Work Reflexivity

Variables	B's team work reflexivity				
	M1	**M2**	**M3**	**M4**	**M5**
Control variables					
B's age	-.02	-.00	-.01	-.00	-.01
B's education	-.11	-.10	-.09	-.06	-.06
A's age	.00	-.00	-.00	-.00	-.00
A's education	-.09	-.02	-.01	-.04	-.03
Dyadic tenure between A and B	.00	-.00	-.00	-.00	-.00
A's higher status than B	$.06^{**}$	.01	-.01	-.00	-.02
Team size	-.00	.04	.04	.04	.04
External task similarity	.10	.08	.10	.10	.12
External interdependence	.28	.10	.08	.05	.04
Team shared goal	.10	-.08	-.11	-.08	-.11
Main effects and mediation effects					
A's task learning					.00
A's contextual learning				$.12^{**}$	$.10^{*}$
A's task knowledge sharing			$.22^{**}$		$.21^{**}$
A's contextual knowledge sharing		$.82^{**}$	$.65^{**}$	$.79^{**}$	$.62^{**}$
Pseudo R^2	.07	.72	.73	.72	.73
Δ Pseudo R^2		.65	.01	.00	.01

Note. N = 633 dyads with 159 members of 37 teams. $^{*}p < .05$, $^{**}p < .01$.

Hypothesis 6c. The results of Model 5 in Table 10 suggested that the effect of Member A's contextual knowledge sharing on Member B's team work reflexivity was positive and significant ($b = .62, p < .01$); meanwhile, the effect of Member A's contextual learning on Member B's team work reflexivity was positive and significant ($b = .10, p < .05$), but the effect was much reduced compared to that when the mediator was not included in the model ($b = .24, p < .01$). These results provided some preliminary support for the hypothesis. Moreover, the results of 20,000 iterations of parameter-based bootstrapping indicated that the indirect effect of Member A's contextual learning on Member B's team work reflexivity through Member's A contextual knowledge sharing was positive and had a 95% CI excluding zero (indirect effect = .102; 95% CI: [.037, .169]). These results provided support for Hypothesis 6c.

Hypothesis 7. The results of Model 2 in Table 11 indicated that the density of task knowledge utilization was positively but not significantly related to team performance (*b* = .02, *n.s.*). Therefore, Hypothesis 7 was not supported.

Hypothesis 8. As can be seen in Model 3 in Table 11, the density of team work reflexivity was positively but not significantly related to team performance (*b* = .20, *n.s.*). Therefore, Hypothesis 8 was not supported.

Table 11. Results of Regression Analyses Predicting Team Performance

Variables	**Team performance**		
	M1	**M2**	**M3**
Control variables			
Team size	-.03	-.03	-.03
External task similarity	.14	.13	.12
External interdependence	-.28	-.29	-.33
Team shared goal	.15	.14	.12
Main effects			
Density of task knowledge utilization		.02	
Density of team work reflexivity			.20
R^2	.07	.07	.09
ΔR^2		.00	.02

Note. N = 37. $^{*}p < .05$, $^{**}p < .01$.

Discussion

Drawing on the framework of team receptivity to personnel movement, in this study I attempted to investigate how the different types of knowledge acquired by an individual team member's external learning were disseminated within teams and further integrated into team-level performance. More specifically, I proposed and found that Member A's task learning was positively and indirectly associated with Member B's task knowledge utilization through Member A's task knowledge sharing, while Member A's contextual learning was positively and indirectly related to Member B's team work reflexivity through Member A's contextual knowledge sharing.

The implications of these findings are twofold. First, by revealing the micro-dynamics in the dyads that link Member A's external learning to Member B's receptive reactions, I explicitly disclose the previously assumed within-team processes sparked by a particular team member's external learning. These findings also partially address the primary research question concerning how the knowledge acquired by a particular team member's external learning is disseminated within teams. Second, by finding that Member A's task learning was related to Member B's task knowledge utilization whereas Member A's contextual learning was associated with Member B's team work reflexivity, I highlight the distinctions between task and contextual learning in terms of their functions as well as contributing to the theoretical underpinnings of the two-facet model of external learning.

Moreover, despite hypothesizing that the density of task knowledge utilization and the density of team work reflexivity were positively related to team performance, neither of these hypotheses were supported. It is likely that the small sample size at the team level ($N = 37$) prevented the discovery of the significant relationships between the two aggregated variables and team performance. As suggested by the correlational coefficients in Table 5 and the regression coefficients in Table 11, all of them were positive though not large enough to be significant. In other words, the pattern of the relationships was consistent with my expectations. To further examine the relationships at team level and to constructively replicate the relationships at relational level, I conducted another study that is introduced and explained in the next chapter.

CHAPTER 5: STUDY 3

In Study 2, I proposed and tested a dual-path and bottom-up model of the relationship between the external learning of individual team members and team-level performance. The findings supported most of the hypotheses except that the aggregated task knowledge utilization and team work reflexivity were not significantly related to team performance. In so doing, I made two novel theoretical contributions. First, I disclosed the previously assumed microdynamics regarding how the knowledge brought by a particular team member's external learning behavior is disseminated and integrated within teams. Second, I advanced the theoretical underpinnings of the classifications of external learning by revealing that different forms of external learning trigger different receptive dynamics among team members.

Study 3 was designed to extend Study 2 in two ways. First, I sought to constructively replicate Study 2 by testing the model in another larger sample and by using an alternative operationalization of external learning. Specifically, I averaged the ratings of task and contextual learning assigned to a particular team member by all the other teammates to derive each member's external learning score. I did so because the averaged scores might reflect the frequency of a particular team member's task and contextual learning behaviors in a more objective way (e.g., van der Vegt, Bunderson, & Oosterhof, 2006). Modeling the two forms of external learning as individual-level variables challenges the robustness of the Study 2 findings across the contexts and operationalizations of key constructs, which improves the value of the replication (Schmidt, 2009). The second major objective of Study 3 was to incorporate a theory-relevant contingency, team performance pressure (i.e., the extent to which a team is accountable for delivering high-quality outcomes; Gardner, 2012; Mitchell, Baer, Ambrose, Folger, & Palmer, 2018), into the model. Specifically, in Study 3, I examined the notion that performance pressure imposed upon a team might serve as an important contextual factor by shaping the aforementioned microdynamics within the team.

Team performance pressure is quite relevant to my conceptual model in two ways. First, Bresman (2010) revealed in his seminal work that the effect of task learning was conditional on team internal learning, while the effect of contextual learning was independent of contingent factors. The author suggested this difference might result from the different levels of complexity involved in these two forms of external learning. I argue that team performance pressure is a theory-relevant moderator that might demonstrate and explicate this difference by boosting the motivation of team members to handle the different levels of complexity involved in different forms of external learning (e.g., Gardner, 2012; Zhang, Jex, Peng, & Wang, 2017). Second, the framework of team receptivity to personnel movement also suggests that the mere presence of personnel movement in itself can lead to team work reflexivity in a straightforward way (Kane & Rink, 2017). In contrast, this framework also suggests that the process of task knowledge utilization does not automatically occur and might be subjected to some contingencies (Rink et al., 2013). Specifically, prior studies in line with this framework have revealed that team members are more likely to utilize the knowledge imported by personnel movement when the team has experienced relatively poor performance during the prior period (e.g., Bunderson, van der Vegt, & Sparrowe, 2013; Choi & Levine, 2004; Hansen, 1999).

Building upon and extending the team receptivity framework, I introduce team performance pressure as a theory-relevant moderator which would accentuate the connections between A's task learning, A's task knowledge sharing, and B's task knowledge utilization. Moreover, because of the more straightforward pattern associated with the effect of contextual learning and the process leading to team work reflexivity, as evidenced by the aforementioned theoretical framework and empirical studies (Bresman, 2010; Rink, et al., 2013), I do not expect team performance pressure to moderate the connections between A's contextual learning, A's contextual knowledge sharing, and B's team work reflexivity.

Theory and Hypotheses

Team performance pressure is a specific type of pressure resulting from the team members' shared belief that the delivery of a superior performance outcome is demanded and that this performance will be linked to significant consequences (Gardner, 2012; Gutnick, Walter, Nijstad, & de Dreu, 2012; Mitchell et al., 2018). Team members experiencing high performance pressure believe that meeting and exceeding performance demands will lead to benefits, such as accolades and promotions, whereas failing to meet these demands may result in some drawbacks such as probation and termination (e.g., Mitchell et al., 2018; Mitchell, Greenbaum, Vogel, Mawritz, & Keating, 2018). As characterized by previous studies (e.g., Gutnick et al., 2012; Mitchell et al., 2018), team performance pressure is a mixture of high expectations and significant consequences, which may have twofold implications for the motivation and behaviors of the members of working teams.

First, team performance pressure highlights to the team members that their current efforts are inadequate for achieving what is demanded. In order to solve the problems associated with performance inadequacy, team members are motivated to exert more effort and stretch their capabilities to better perform their jobs (e.g., Eisenberger & Aselage, 2009; Sitkin, See, Miller, Lawless, & Carton, 2011). Second, team performance pressure also involves scrutiny with a high-stakes manner and may result in harmful consequences, which may also promote the physiological arousal and negative emotions of the team members (e.g., Forward & Zander, 1971; Gardner, 2012). To avoid the potential losses and the associated negative experiences, team members need to be motivated to exhibit persistence and perseverance during the completion of team work, especially in the face of difficulties (e.g., Carr & Steele, 2009; Gutnick et al., 2012). On top of these two implications that team performance pressure has for the team members' motivations and behaviors, I explicate how team performance pressure accentuates the connections between A's task learning, A's task knowledge sharing, and B's task knowledge utilization as follows.

Influence of Team Performance Pressure on Task Learning–Task Knowledge Sharing Linkage

I first argue that team performance pressure would strengthen the positive relationship between A's task learning and A's task knowledge sharing in two ways. First, as suggested by the aforementioned discussion, higher team performance pressure signals to team members that new procedures and methods should be adopted by the team in order to address the problems associated with inadequate performance (e.g., Eisenberger & Aselage, 2009; Sitkin et al., 2011). Under this condition, if Member A obtains some task-relevant knowledge which could help the team avoid reinventing the wheel and repeating mistakes, it is more likely that s/he will share that knowledge with Member B (e.g., Gardner, 2012; Kou & Stewart, 2018), as knowledge sharing is the first step in the relevant knowledge being disseminated and integrated into team performance (e.g., Barton & Bunderson, 2014; Bunderson, 2003). Second, the heightened scrutiny and significant consequences associated with higher team performance pressure also motivate team members to exhibit persistence and perseverance in team work, especially during difficult times. As such, even though the transfer of task-relevant knowledge involves some complexities and difficulties (Bresman, 2010), Member A experiencing higher team performance pressure would tirelessly explain the knowledge to Member B with great patience (e.g., de Dreu, 2007; van Hiel & Schittekatte, 1998).

In contrast, when team performance pressure is lower, Member A will not feel it is necessary to exert more effort to enhance the team performance, nor will s/he exhibit persistence and perseverance during the more difficult times of team work. As a result, it is less likely that Member A will share the knowledge s/he obtains from outside by engaging in task learning with Member B. In sum, I propose the following hypothesis:

Hypothesis 9: Team performance pressure moderates the positive relationship between Member A's task learning and Member A's task knowledge sharing such that the relationship is more positive when team performance pressure is higher.

Influence of Team Performance Pressure on Task Knowledge Sharing–Task Knowledge Utilization Linkage

Similarly, I argue that the positive relationship between A's task knowledge sharing and B's task knowledge utilization is stronger when the team performance pressure is higher for two reasons. First, team members who experience higher team performance pressure believe their current efforts and practices are not sufficient and that they must stretch their capabilities to enhance the team performance (e.g., Mitchell et al., 2018). However, in many circumstances it is not easy or efficient for teams to generate the necessary knowledge all by themselves (e.g., Argote & Ingram, 2000). Under this condition, if Member B is confronted with the task-relevant knowledge that is shared by another Member A and that is potentially beneficial for their completion of team work, s/he is very likely to adopt and utilize the knowledge. In support of this argument, previous studies have revealed that team members are more willing to accept the knowledge imported by personnel movement when the team is experiencing a relatively poor performance (e.g., Choi & Levine, 2004). Second, higher team performance pressure and its potentially harmful consequences render team members more alert, thereby, enhancing their persistence and perseverance during knowledge transfer (e.g., Rousseau, 1997). As a result, Member B experiencing higher team performance pressure will concentrate on the absorption of the task-relevant knowledge shared by another Member A (e.g., Eisenberger & Aselage, 2009). Moreover, s/he will be less likely to be distracted by other stimuli and abandon the knowledge utilization, even though some complicated tactical issues are involved in the transfer processes (e.g., Bresman, 2010, 2013).

In contrast, when the performance pressure experienced by team members is lower, Member B will not feel it is necessary to adopt new practices to enhance their team performance, nor will s/he exhibit persistence and perseverance when facing difficulties during the process of knowledge transfer. As a result, it is less likely that Member B will utilize the knowledge shared by another Member A. Therefore, I propose the following hypothesis:

Hypothesis 10: Team performance pressure moderates the positive relationship between Member A's task knowledge sharing and Member B's task knowledge utilization such that the relationship is more positive when team performance pressure is higher.

An Integrated Model

In this study, I have hypothesized that team performance pressure moderates the mediated task learning–task knowledge utilization relationship. Moderated mediation occurs "*when the strength of an indirect effect depends on the level of some variable, or, in other words, when mediation relations are contingent on the level of a moderator*" (Preacher, Rucker, & Hayes, 2007: 193). As such, the two specific accentuating moderation effects for each stage add up to the overall moderated mediation effects. The extended conceptual model is illustrated in Figure 7.

> *Hypothesis 11: Team performance pressure moderates the positive indirect relationship between Member A's task learning and Member B's task knowledge utilization through Member A's task knowledge sharing such that the relationship is more positive when team performance pressure is higher.*

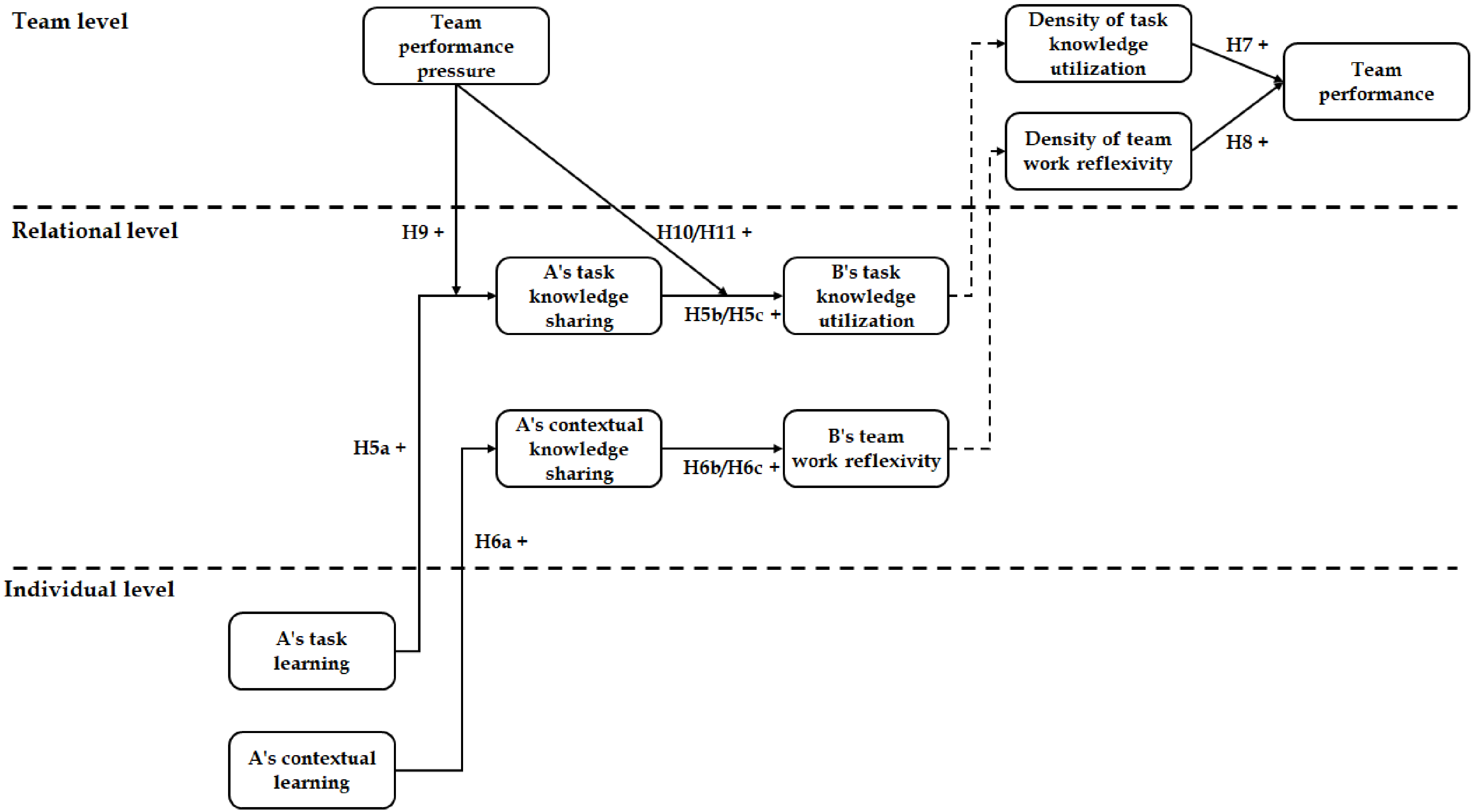

Figure 7. The extended conceptual model in Study 3

Method

Sample and Procedure

In Study 3, I collected data from teams in a financial company located in eastern China. The main business of the company is providing peer-to-peer lending services to the public and organizations. Similarly to the research context in Study 2, the company had already adopted teams as the basic operational units in order to manage the complexities and uncertainties arising from the tasks and the environment in which they operated. The team members' daily work in this company was also highly interdependent and required frequent interactions. They generally needed to cross their team boundaries to learn from the outside. Moreover, the teams had regular meetings, in which they could share, discuss, and integrate information from diverse sources outside of the team boundary. Additionally, as a result of the economic downturn and the imposition of strict government policies in past years, all the teams in the company were facing team performance pressure to some extent. Therefore, this sample also provided an appropriate setting for testing the hypothetical model.

Similar to the design of Study 2, I collected data in two waves with a one-month time lag. Similarly, I obtained the roster of the team members and leaders before the data collection. Specifically, 244 members and their leaders from 65 teams were invited to participate in the study. Consistent with Study 2, at Time 1, I asked every team member to answer questions regarding the task and contextual learning activities engaged in by each of his or her teammates with the round-robin method (Kenny, 1994). At Time 2, using the same round-robin approach, I asked every team member to answer questions regarding the task and contextual knowledge sharing from each peer as well as his or her own task knowledge utilization and team work reflexivity activities when interacting with each peer in the same team. At the same time, I also required the team members to report any team performance pressure and the team leaders to evaluate the performances of the teams they supervised.

Among the 244 team members, 197 responded to the multi-wave questionnaires in their entirety, with a response rate of 81%. Among the 65 team leaders, 58 responded to the measures of team performance completely, with a response rate of 89%. Again, I imputed the missing values by following the procedure suggested by Schönbrodt et al. (2012). The resulting final sample consisted of 698 dyads among 225 members in 60 teams. Within the final sample of team members, 53% were male, the mean age was 28.30 years (standard deviation = 3.33), and the majority had a bachelor's degree (79%).

Measures

I set up the survey in Study 3 using a procedure similar to that for Study 2, while for the replication part of Study 3, I also used the same scales to measure the variables at relational and team levels, with two noteworthy differences. First, as mentioned earlier, to reflect the frequency of a particular team member's task and contextual learning behaviors in a more objective way (e.g., van der Vegt et al., 2006), I averaged the ratings of task and contextual learning assigned to a particular team member by all the other teammates in order to derive each member's external learning score. As such, I was able to cross validate the findings from different studies (Schmidt, 2009). Second, given that both male and female participants were involved in this study and prior studies have revealed that the female team members were subjected to some disadvantages during the knowledge exchange and utilization processes (e.g., Joshi & Knight, 2015; Thomas-Hunt & Phillips, 2004), I included both A and B's genders as control variables. In addition to these variables in the replication component, I described the measures of the unique variables in Study 3 (i.e., team performance pressure) as follows.

Team performance pressure (Time 2). I adapted the four-item scale originally developed by Mitchell et al. (2018) to measure team performance pressure. On a seven-point Likert scale, the team members were required to evaluate the extent to which they collectively felt that their performance efforts would be scrutinized in a high-stakes manner. A sample item was "*The pressures for performance in my team are high.*" The Cronbach's alpha for this scale was .72.

Given that team performance pressure was measured at an individual level while being analyzed as a team-level contextual variable, I calculated within-group agreement (e.g., R_{wg} and Average Deviation Index; Burke et al., 2006; James, Demaree, & Wolf, 1984) and team-mean reliability (e.g., ICC [1] and ICC [2];

Bliese, 2000) to justify the aggregation of data from the individual level to the team level. The results revealed that the mean of R_{wg} was .89 and the median R_{wg} was .94, both of which were higher than the traditional threshold (i.e., .70; Lebreton, Burgess, Kaiser, Atchley, & James, 2003). Additionally, the mean of the average deviation index across all the teams for team performance pressure was .63, which was lower than the threshold when a seven-point Likert scale was used (i.e., 1.17; Burke et al., 1999). All these results reflected a substantive degree of agreement among the members from the same teams in their ratings of team performance pressure.

Furthermore, I estimated the team-mean reliability by calculating ICC (1) and ICC (2) of team performance pressure. I first conducted an ANOVA to ascertain whether there were sufficient variances between the teams with regard to this measure. The results from the analyses confirmed that there were significant differences between the teams in team performance pressure ($F = 3.21$, $p < .01$). Moreover, the ICC (1) and ICC (2) for team performance pressure were .37 and .69, respectively, which were located in the range of ICC (1) and ICC (2) values across different team-level constructs according to Woehr, Loignon, Schmidt, Loughry, and Ohland's (2015) extensive review. Taken together, these results provided sufficient support for the aggregation of team performance pressure.

Analytic Strategy

Similar to Study 2, I conducted the analyses in three steps: CFAs, variance decomposition, and hypotheses testing. To further confirm the hypotheses regarding the mediation effects, I also adopted the parameter-based bootstrapping approach to estimate the 95% confidence intervals of the effects (Preacher & Selig, 2012). Equally, the CFAs were performed with *Mplus* 8.0 (Muthén & Muthén, 2017), the hypotheses at relational level were analyzed with R package *pdSRM* (Knight & Humphrey, 2019), and the hypotheses at team level were examined with linear regression models in SPSS.

Results

Descriptive Statistics and Confirmatory Factor Analyses

Consistent with Study 2, I present the means, standard deviations, and correlations of the variables at each level, respectively. Table 12 shows the descriptive statistics at relational level while Table 13 displays the descriptive statistics at team level.

Table 12. Means, Standard Deviation and Correlates among Variables at Relational Level

Variables	Mean	SD	1	2	3	4	5	6	7	8	9	10
1. B's gender	1.46	.50	—									
2. B's age	28.29	3.34	-.17	—								
3. B's education	2.97	.49	.01	.09	—							
4. A's gender	1.46	.50	.27	-.02	.06	—						
5. A's age	28.29	3.34	-.02	.10	.05	-.17	—					
6. A's education	2.97	.49	.06	.05	.15	.01	.09	—				
7. Dyadic tenure between A and B	8.53	7.18	-.02	-.03	-.22	-.04	-.01	-.20	—			
8. A's higher status than B	.00	.96	.00	-.09	.03	.00	.09	-.03	.03	(.89)		
9. Team size	4.89	.69	-.06	.00	-.04	-.06	.00	-.04	.14	.00	—	
10. External task similarity	4.75	.78	.03	-.03	.10	.03	-.03	.10	-.27	.00	.05	—
11. External interdependence	5.99	.49	.01	-.09	.04	.01	-.09	.04	.09	.00	-.03	.04
12. Team shared goal	5.97	.48	-.10	.11	.02	-.10	.11	.02	-.10	.00	-.12	.22
13. A's task learning	3.18	.74	-.12	.02	.02	-.11	.05	-.02	.00	.31	-.14	.20
14. A's contextual learning	3.19	.71	-.09	.04	.00	-.07	.02	-.04	-.06	.23	-.21	.16
15. A's task knowledge sharing	3.20	.99	-.10	-.02	.07	-.09	.07	.01	.04	.23	-.13	.12
16. A's contextual knowledge sharing	3.01	1.03	-.10	.06	.10	-.10	.07	.07	-.05	.16	-.10	.15
17. B's task knowledge utilization	3.02	.94	-.12	-.02	.06	-.08	.05	.01	.02	.24	-.04	.17
18. B's team work reflexivity	3.00	.93	-.15	-.03	.05	-.13	.09	.05	-.04	.21	-.11	.14
19. Team performance pressure	4.80	.59	-.17	.19	.09	-.17	.19	.09	-.14	.00	-.10	.24

Note. N = 698 dyads with 225 members of 60 teams. Variables at individual and team levels were assigned to relational level.

Correlations no less than |.08| are significant at p < .05, and correlations no less than |.10| are significant at p < .01.

Table 12 Means, Standard Deviation and Correlates among Variables at Relational Level (Continued)

Variables	11	12	13	14	15	16	17	18	19
11. External interdependence	(.84)								
12. Team shared goal	.63	(.89)							
13. A's task learning	.33	.46	(.97)						
14. A's contextual learning	.28	.47	.83	(.92)					
15. A's task knowledge sharing	.29	.30	.48	.45	(.97)				
16. A's contextual knowledge sharing	.25	.33	.46	.48	.81	(.95)			
17. B's task knowledge utilization	.29	.31	.45	.42	.83	.77	(.96)		
18. B's team work reflexivity	.26	.31	.42	.43	.74	.83	.82	(.95)	
19. Team performance pressure	.12	.23	.26	.27	.23	.27	.22	.22	(.72)

Note. $N = 698$ *dyads with 225 members of 60 teams. Variables at individual and team levels were assigned to relational level.*

Correlations no less than $|.08|$ *are significant at* $p < .05$*, and correlations no less than* $|.10|$ *are significant at* $p < .01$*.*

Table 13. Means, Standard Deviation and Correlates among Variables at Team Level

Variables	**Mean**	**SD**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
1. Team size	3.75	1.16	—							
2. External task similarity	4.75	.82	.00	—						
3. External interdependence	6.03	.51	-.16	.01	(.84)					
4. Team shared goal	6.01	.47	-.16	.07	.67**	(.89)				
5. Density of task knowledge utilization	3.07	.59	-.14	.34**	.50**	.43**	—			
6. Density of team work reflexivity	3.11	.63	-.30*	.26*	.45**	.43**	.89**	—		
7. Team performance pressure	4.89	.69	-.23	.00	.19	.24	.26*	.32*	(.72)	
8. Team performance	5.44	.78	-.23	-.10	.13	.07	.34**	.35**	.09	(.81)

*Note. N = 60. * $p < 0.05$; ** $p < 0.01$. The figures on the diagonal in parentheses are the alpha coefficients.*

I also conducted two groups of CFAs at the two different levels. First, I conducted CFAs on the seven variables rated by the team members with the round-robin design (i.e., status, task learning, contextual learning, task knowledge sharing, contextual knowledge sharing, task knowledge utilization, team work reflexivity). The seven-factor model had an acceptable fit (χ^2/df = 2.97, p < .01, *RMSEA* = .05, *CFI* = .98, *TLI* = .98, *SRMR* = .02). This model also fitted the data better than alternative models when the following variables were combined: (1) task learning and contextual learning ($\Delta\chi^2/\Delta df$ = 81.90, p < 0.01); (2) task knowledge sharing and contextual knowledge sharing ($\Delta\chi^2/\Delta df$ = 180.76, p < 0.01); (3) task knowledge utilization and team work reflexivity ($\Delta\chi^2/\Delta df$ = 161.71, p < 0.01); (4) the aforementioned three pairs of constructs, respectively ($\Delta\chi^2/\Delta df$ = 159.97, p < 0.01); (5) the variables measured at Time 1 and the variables measured at Time 2, respectively ($\Delta\chi^2/\Delta df$ = 188.71, p < 0.01); and (6) all of the variables ($\Delta\chi^2/\Delta df$ = 365.50, p < 0.01).

Second, I conducted CFAs on the three multiple-item variables reported by the team members (i.e., external interdependence, team shared goal and team performance pressure). The hypothetical three-factor model also fitted the data well (χ^2/df = 2.58, p < .01, *RMSEA* = .08, *CFI* = .95, *TLI* = .93, *SRMR* = .05). This model also fitted the data better than alternative models when the following variables were combined: (1) the variables measured at Time 1 and the variables measured at Time 2, respectively ($\Delta\chi^2/\Delta df$ = 92.38, p < 0.01); and (2) all of the variables ($\Delta\chi^2/\Delta df$ =

137.35, $p < 0.01$). These results indicated that the measures captured distinct constructs.

Variance Decomposition

Consistent with Study 2, I first ran a series of null models to decompose the variance of the dependent variables (i.e., task knowledge sharing, contextual knowledge sharing, task knowledge utilization and team work reflexivity) into team, actor (B), partner (A), and dyad components. Table 14 presents the results of this variance decomposition. Similar to what I found in Study 2, the dyad-level component was also substantial for task knowledge sharing (24%), contextual knowledge sharing (21%), task knowledge utilization (30%), and team work reflexivity (27%). In line with prior research and the findings in Study 2, individual-level dynamics also contributed to variance in task knowledge sharing (actor [B] = 39%, partner [A] = 12%), contextual knowledge sharing (actor [B] = 46%, partner [A] = 8%), task knowledge utilization (actor [B] = 36%, partner [A] = 12%), and team work reflexivity (actor [B] = 37%, partner [A] = 12%). Consistent with previous studies on the team-level antecedents of individual knowledge sharing processes and the results revealed in Study 2, team-level components also influenced variances in task knowledge sharing (25%), contextual knowledge sharing (25%), task knowledge utilization (21%), and team work reflexivity (24%). The results of the variance decomposition show the necessity of analyzing the data with the social relations model.

Table 14. Results of Social Relations Model Variance Decomposition

Sources	A's task knowledge sharing		A's contextual knowledge sharing		B's task knowledge utilization		B's team work reflexivity	
	Variances	*Percentages (%)*	*Variances*	*Percentages (%)*	*Variances*	*Percentages (%)*	*Variances*	*Percentages (%)*
Group	0.26	25	0.28	25	0.19	21	0.23	24
Actor	0.41	39	0.52	46	0.34	36	0.35	37
Partner	0.12	12	0.09	8	0.11	12	0.11	12
Dyad	0.26	24	0.23	21	0.28	30	0.25	27

Note. N = 698 dyads with 225 members of 60 teams.

Hypotheses Testing

Hypothesis 5a. In support of Hypothesis 5a, Model 3 in Table 15 indicated that Member A's task learning was significantly and positively related to Member A's task knowledge sharing (b = .30, p < .01), even if Member A's contextual learning was simultaneously included.

Table 15. Results of SRM Predicting A's Task Knowledge Sharing

Variables	A's task knowledge sharing						
	M1	M2	M3	M4	M5	M6	M7
Control variables							
B's gender	-.10	-.08	-.08	-.06	-.06	-.06	-.06
B's age	-.02	-.02	-.02	-.02	-.02	-.02	-.02
B's education	.13	.12	.13	.11	.12	.12	.12
A's gender	-.02	-.01	-.01	-.01	-.00	-.01	-.01
A's age	.01	.01	.01	.01	.01	.00	.01
A's education	.03	.04	.05	.04	.04	.04	.04
Dyadic tenure	.01**	.01	.01	.01	.01	.01	.01
A's higher status than B	.15**	.07*	.06	.07*	.07	.07*	.07
Team size	-.15*	-.10	-.08	-.09	-.07	-.09	-.07
External task similarity	.15	.11	.11	.09	.09	.10	.11
External interdependence	.38*	.32*	.34*	.30	.32*	.28	.30*
Team shared goal	.29	.05	-.01	.04	-.02	.04	-.01
Main effects							
A's task learning		.43**	.30**	.42**	.29**	.42**	.30**
A's contextual learning			.20*		.19*		.19*
Team performance pressure				.15	.14	.11	.11
Interaction effects							
A's task learning × Team performance pressure						.16*	.18
A's contextual learning × Team performance pressure							-.05
Pseudo R^2	.18	.28	.29	.28	.29	.29	.29
Δ Pseudo R^2		.10	.01	.00	.01	.01	.00

Note. N = 698 dyads with 225 members of 60 teams. $^{*}p < .05$, $^{**}p < .01$.

Hypothesis 5b. As can been seen in Model 3 in Table 16, Member A's task knowledge sharing was significantly and positively related to Member B's task knowledge utilization (b = .56, p < .01), even if Member A's contextual knowledge sharing was simultaneously included. Therefore, Hypothesis 5b was supported.

Table 16. Results of SRM Predicting B's Task Knowledge Utilization

Variables	**B's task knowledge utilization**				
	M1	**M2**	**M3**	**M4**	**M5**
Control variables					
B's gender	-.15	-.08	-.06	-.07	-.06
B's age	-.01	-.00	-.01	-.00	-.01
B's education	.11	.01	-.00	.01	-.01
A's gender	-.01	.01	.02	.01	.02
A's age	-.01	-.01	-.01	-.01	-.01
A's education	.04	.02	-.01	.02	-.01
Dyadic tenure	.01**	.00	.00	.00	.00
A's higher status than B	.15**	.04	.04*	.04	.04
Team size	-.05	.07*	.07*	.07*	.07*
External task similarity	.22**	.10*	.10*	.10*	.10*
External interdependence	.35*	.06	.08	.06	.07
Team shared goal	.27	.07	.00	.05	-.00
Main effects and mediation effects					
A's task learning				.04	.04
A's contextual learning					-.02
A's task knowledge sharing		.75**	.56**	.74**	.56**
A's contextual knowledge sharing			.26**		.26**
Pseudo R^2	.17	.71	.73	.71	.73
Δ Pseudo R^2		.54	.02	.00	.02

Note. N = 698 dyads with 225 members of 60 teams. $^{*}p < .05$, $^{**}p < .01$.

Hypothesis 5c. The results of Model 5 in Table 16 suggested that the effect of Member A's task knowledge sharing on Member B's task knowledge utilization was positive and significant (b = .56, p < .01), while the effect of Member A's task learning on Member B's task knowledge utilization was positive but not significant (b = .04, *n.s.*). These results provided some preliminary support for the hypothesis. To further confirm the mediation effect, I calculated the indirect effect of Member

A's task learning on Member B's task knowledge utilization through Member's A task knowledge sharing and estimated its 95% confidence interval with 20,000 parameter-based bootstrapping (Preacher & Selig, 2012). The results indicated that the indirect effect was positive and had a 95% CI excluding zero (indirect effect = .167; 95% CI: [.074, .262]). These results provided support for Hypothesis 5c.

Hypothesis 6a. In support of Hypothesis 6a, Model 3 in Table 17 indicated that Member A's contextual learning was significantly and positively related to Member A's contextual knowledge sharing (b = .32, p < .01), even when Member A's task learning was simultaneously included.

Table 17. Results of SRM Predicting A's Contextual Knowledge Sharing

Variables	A's contextual knowledge sharing						
	M1	M2	M3	M4	M5	M6	M7
Control variables							
B's gender	-.11	-.10	-.10	-.08	-.07	-.08	-.07
B's age	-.00	.00	.00	.00	.00	.00	-.00
B's education	.15	.15	.14	.14	.14	.14	.14
A's gender	-.06	-.06	-.06	-.05	-.05	-.05	-.06
A's age	-.01	-.00	-.00	-.00	-.00	-.00	-.00
A's education	.14*	.16*	.16*	.15*	.15*	.16*	.15*
Dyadic tenure	.01	.00	.00	.01	.00	.01	.01
A's higher status than B	.09**	.03	.02	.03	.02	.03	.02
Team size	-.12	-.05	-.05	-.04	-.04	-.03	-.04
External task similarity	.12	.10	.10	.09	.08	.09	.10
External interdependence	.19	.20	.19	.18	.17	.18	.16
Team shared goal	.44*	.18	.17	.16	.16	.17	.15
Main effects							
A's task learning			.12		.11		.11
A's contextual learning		.41**	.32**	.40**	.32**	.40**	.32**
Team performance pressure				.17	.16	.16	.14
Interaction effects							
A's task learning × Team performance pressure							.21
A's contextual learning × Team performance pressure						.04	-.13
Pseudo R^2	.11	.25	.25	.26	.26	.26	.26
Δ Pseudo R^2		.14	.00	.01	.00	.00	.00

Note. N = 698 dyads with 225 members of 60 teams. $^{*}p < .05$, $^{**}p < .01$.

Hypothesis 6b. As can been seen in Model 3 in Table 18, Member A's contextual knowledge sharing was significantly and positively related to Member B's team work reflexivity (b = .63, p < .01), even if Member A's task knowledge sharing was simultaneously included. Therefore, Hypothesis 6b was supported.

Table 18. Results of SRM Predicting B's Team Work Reflexivity

Variables	**B's team work reflexivity**				
	M1	**M2**	**M3**	**M4**	**M5**
Control variables					
B's gender	$-.26^{*}$	$-.18^{**}$	$-.17^{**}$	$-.18^{**}$	$-.17^{**}$
B's age	-.02	$-.02^{*}$	-.02	$-.02^{*}$	-.02
B's education	.07	-.04	-.04	-.04	-.04
A's gender	-.06	-.02	-.02	-.02	-.02
A's age	.01	$.01^{*}$	.01	$.01^{*}$	.01
A's education	$.14^{*}$	.04	.05	.04	.04
Dyadic tenure	$.01^{*}$	.00	.00	.00	.00
A's higher status than B	$.13^{**}$	$.07^{**}$	$.05^{*}$	$.07^{**}$	$.06^{**}$
Team size	$-.13^{*}$	-.05	-.03	-.05	-.04
External task similarity	$.16^{*}$	.07	.06	.07	.06
External interdependence	.28	.13	.10	.13	.09
Team shared goal	.31	-.01	-.01	-.00	.01
Main effects and mediation effects					
A's task learning					.00
A's contextual learning				-.02	-.04
A's task knowledge sharing			$.14^{**}$		$.14^{**}$
A's contextual knowledge sharing		$.73^{**}$	$.63^{**}$	$.73^{**}$	$.64^{**}$
Pseudo R^2	.18	.71	.72	.71	.72
Δ Pseudo R^2		.53	.01	.00	.01

Note. N = 698 dyads with 225 members of 60 teams. $^{*}p < .05$, $^{**}p < .01$.

Hypothesis 6c. The results of Model 5 in Table 18 suggested that the effect of Member A's contextual knowledge sharing on Member B's team work reflexivity was positive and significant (b = .64, p < .01), while the effect of Member A's contextual learning on Member B's team work reflexivity was negative but not significant (b = -.04, *n.s.*). These results provided some preliminary support for the hypothesis. Moreover, the results of 20,000 iterations of parameter-based bootstrapping indicated that the indirect effect of Member A's contextual learning on Member B's team work reflexivity through Member's A contextual knowledge sharing was positive and had a 95% CI excluding zero (indirect effect = .205; 95% CI: [.092, .321]). These results provided support for Hypothesis 6c.

Hypothesis 7. The results of Model 2 in Table 19 indicated that the density of task knowledge utilization was positively and significantly related to team performance (b = .62, p < .01). Therefore, Hypothesis 7 was supported.

Hypothesis 8. As can be seen in Model 3 in Table 19, the density of team work reflexivity was positively and significantly related to team performance (b = .50, p < .01). Therefore, Hypothesis 8 was supported.

Table 19. Results of Regression Analyses Predicting Team Performance

Variables	**Team performance**		
	M1	**M2**	**M3**
Control variables			
Team size	-.14	-.13	-.08
External task similarity	-.09	-.24	-.19
External interdependence	.19	-.11	.02
Team shared goal	-.06	-.16	-.20
Main effects			
Density of task knowledge utilization		$.62^{**}$	
Density of team work reflexivity			$.50^{**}$
$\mathbf{R^2}$	.07	$.21^{*}$	$.18^{*}$
$\mathbf{\Delta R^2}$		$.14^{*}$	$.11^{*}$

Note. N = 60. $^{*}p < .05$, $^{**}p < .01$.

Hypothesis 9. The results of Model 7 in Table 15 indicated that the interaction effect between A's task learning and team performance pressure on A's task knowledge sharing was positive but not significant (b = .18, *n.s.*). Therefore, Hypothesis 9 was not supported. Moreover, as can be seen in Model 7 in Table 17, the interaction effect between A's contextual learning and team performance pressure on A's contextual knowledge sharing was negative but not significant (b = -.13, *n.s.*), which was consistent with my expectation that team performance pressure does not moderate the contextual learning–contextual knowledge sharing relationship.

Hypothesis 10. As can be seen in Model 7 in Table 20, the interaction effect between A's task knowledge sharing and team performance pressure on B's task knowledge utilization was positive and significant (b = .18, p < .01). Following Cohen et al. (2003), I plotted this significant interaction using two levels of team performance pressure (i.e., +1 SD and –1 SD) in Figure 8. A simple slopes test indicated that A's task knowledge sharing was positively related to B's task knowledge utilization at higher levels of team performance pressure (β = .66, p < .01); meanwhile, the effect of the relationship was much reduced though still significant at lower levels of team performance pressure (β = .45, p < .01). Moreover, the results of 20,000 iterations of parameter-based bootstrapping of difference between the slopes at higher and lower levels of team performance pressure were positive and significant (difference = .21; 95% CI: [.125, .409]). These results together supported Hypothesis 10.

Additionally, as can be seen in Model 7 in Table 21, the interaction effect between A's contextual knowledge sharing and the team performance pressure on B's team work reflexivity was positive but not significant (b = *.05*, *n.s.*), which was consistent with my expectation that team performance pressure does not moderate the contextual knowledge sharing–team work reflexivity relationship.

Table 20. Results of SRM Predicting B's Task Knowledge Utilization

Variables	B's task knowledge utilization						
	M1	M2	M3	M4	M5	M6	M7
Control variables							
B's gender	-.15	-.07	-.07	-.06	-.06	-.05	-.05
B's age	-.01	-.00	-.01	-.00	-.00	-.01	-.01
B's education	.11	.01	-.00	.01	.01	-.00	-.01
A's gender	-.01	.01	.02	.01	.01	.02	.03
A's age	-.01	-.01	-.01	-.01	-.01	-.01	-.01
A's education	.04	.02	-.01	.02	.02	-.01	-.01
Dyadic tenure	.01**	.00	.00	.00	.00	.00	.00
A's higher status than B	.15**	.04	.04*	.04	.04	.05*	.04
Team size	-.05	.07*	.07*	.07*	.07*	.07*	.07*
External task similarity	.22**	.10*	.10*	.09*	.09*	.09*	.09*
External interdependence	.35*	.06	.08	.04	.04	.06	.06
Team shared goal	.27	.06	.00	.07	.06	.01	.01
Main effects							
A's task learning					.02		.04
A's contextual learning							-.04
A's task knowledge sharing		.75**	.56**	.74**	.74**	.55**	.55**
A's contextual knowledge sharing			.26**			.26**	.27**
Team performance pressure		.02	-.01	-.01	-.00	-.02	-.02
Interaction effects							
A's task learning × Team performance pressure					-.04		-.06
A's contextual learning × Team performance pressure							.04
A's task knowledge sharing × Team performance pressure				.10**	.11**	.17**	.18**
A's contextual knowledge sharing × Team performance pressure						-.09	-.10
Pseudo R^2	.17	.71	.73	.71	.71	.73	.73
Δ Pseudo R^2		.54	.02	.00	.00	.02	.00

Note. N = 698 dyads with 225 members of 60 teams. $^{*}p < .05$, $^{**}p < .01$.

Table 21. Results of SRM Predicting B's Team Work Reflexivity

Variables	B's team work reflexivity						
	M1	**M2**	**M3**	**M4**	**M5**	**M6**	**M7**
Control variables							
B's gender	-.26*	-.18**	-.17**	-.17**	-.17**	-.16**	-.17**
B's age	-.02	-.02*	-.02	-.02*	-.02*	-.02*	-.02
B's education	.07	-.04	-.04	-.03	-.03	-.03	-.03
A's gender	-.06	-.02	-.02	-.02	-.02	-.02	-.02
A's age	.01	.01*	.01*	.01*	.01	.01	.01
A's education	.14*	.04	.05	.04	.04	.05	.05
Dyadic tenure	.01*	.00	.00	.00	.00	.00	.00
A's higher status than B	.13**	.07**	.05*	.07**	.07**	.05**	.06**
Team size	-.13*	-.05	-.04	-.05	-.05	-.04	-.04
External task similarity	.16*	.07	.06	.07	.07	.06	.05
External interdependence	.28	.13	.10	.12	.11	.09	.08
Team shared goal	.31	-.01	-.01	-.01	.01	-.00	.03
Main effects							
A's task learning							.00
A's contextual learning					-.03		-.05
A's task knowledge sharing			.14**			.14**	.14**
A's contextual knowledge sharing		.73**	.63**	.72**	.73**	.63**	.63**
Team performance pressure		-.01	-.02	-.02	-.04	-.03	-.04
Interaction effects							
A's task learning × Team performance pressure							-.07
A's contextual learning × Team performance pressure					.07		.11
A's task knowledge sharing × Team performance pressure						.04	.04
A's contextual knowledge sharing × Team performance pressure				.08*	.06	.06	.05
Pseudo R^2	.18	.71	.72	.71	.72	.72	.72
Δ Pseudo R^2		.53	.01	.00	.01	.01	.00

Note. N = 698 dyads with 225 members of 60 teams. $^{*}p < .05$, $^{**}p < .01$.

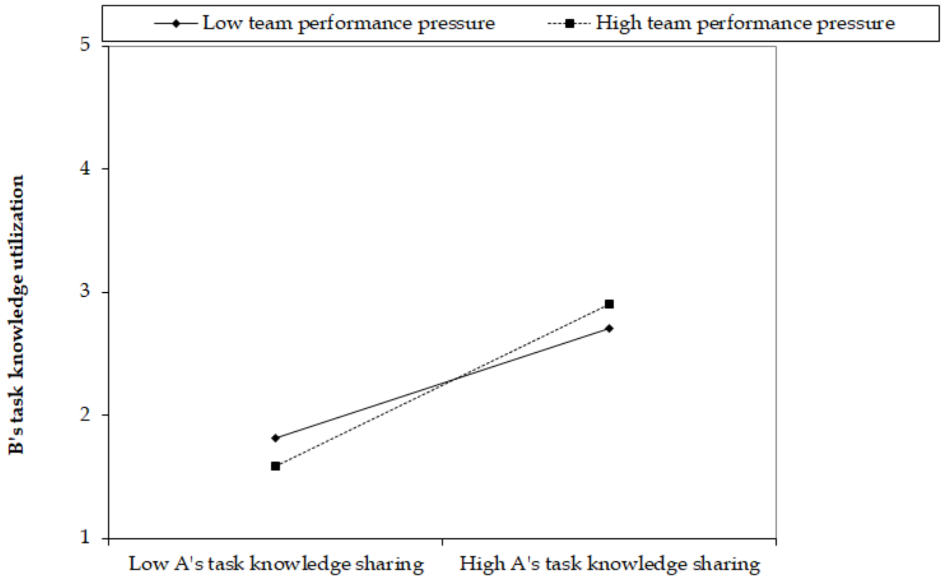

Figure 8. Interaction plot of A’s task knowledge sharing and team performance pressure in predicting B’s task knowledge utilization

Hypothesis 11. To test this hypothesis, at higher and lower levels of team performance pressure, I calculated the indirect effects of Member A’s task learning on Member B’s task knowledge utilization through Member’s A task knowledge sharing and estimated their 95% confidence intervals with 20,000 parameter-based bootstrapping, respectively (Preacher & Selig, 2012). The results indicated that the indirect effect was positive and had a 95% CI excluding zero (indirect effect = .264; 95% CI: [.125,.409]) when team performance pressure was higher; meanwhile, the indirect effect was positive but had a 95% CI including zero (indirect effect = .085; 95% CI: [-.014,.188]) when team performance pressure was lower. These results together supported Hypothesis 11.

Discussion

In this study, I constructively replicated Study 2 by testing the model in another larger sample. Consistent with the findings from Study 2, I found that Member A's task learning was positively and indirectly associated with Member B's task knowledge utilization through Member A's task knowledge sharing, while Member A's contextual learning was positively and indirectly related to Member B's team work reflexivity through Member A's contextual knowledge sharing. Moreover, in this study I revealed that the density of task knowledge utilization and the density of team work reflexivity were positively related to team performance, respectively, thereby, confirming the hypotheses that were not supported in Study 2. Finally, in this study I introduced team performance pressure as a contextual factor that was expected to strengthen the linkages between Member A's task learning, Member A's task knowledge sharing, and Member B's task knowledge utilization. The results indicated that team performance pressure did not moderate the relationship at the first stage but did accentuate the relationship at the second stage. With regard to the moderating effects that were not significant at the first stage, I speculate that this was due to a particular feature of the research context. In the financial company, the team members are highly interdependent upon each other in terms of both tasks and outcomes. As such, it is both necessary and automatic for Member A to share the task-relevant knowledge with Member B when s/he obtains the knowledge.

In sum, this study constructively replicated the findings I revealed at the relational level in Study 2, further linked the relational-level dynamics to the team level with a bottom-up approach and identified team performance pressure as an important team-level contingency to the aforementioned relationship at relational level. In so doing, this study has threefold implications. First, by drawing on the team receptivity framework and validating a bottom-up model, I provide a theoretical account for how and when the knowledge acquired by an individual team member's external learning is disseminated and integrated into a team-level performance. This advances the literature on external learning and boundary spanning by uncovering the previously assumed but seldom investigated mechanisms underlying the link between external activities and team effectiveness (Marrone, 2010). Second, on top of the team receptivity framework, I link different forms of external learning to distinct processes (i.e., task knowledge utilization vs. team work reflexivity), thereby, advancing the theoretical underpinnings of the taxonomy of task versus contextual learning (Bresman, 2010; Harvey et al., 2018). Third, the theorizing and findings associated with the moderating role of team performance pressure qualify the team receptivity framework as a useful theoretical perspective on one hand, while highlighting the distinctions between task and contextual learning on the other hand.

CHAPTER 6: GENERAL DISCUSSION AND CONCLUSION

External learning is an increasingly prevalent activity engaged in by team members that has important implications for team and organizational effectiveness. Despite this prevalence and importance, few studies have been conducted with the aim of understanding the social structural factors leading to the external learning of individuals, along with how the team-level performance implications emerge after individual team members' engage in external learning. To address these research questions, I drew upon social network theory and the framework of team receptivity to personnel movement to construct a bottom-up conceptual model. In this conceptual model, I focused upon the social network antecedents of individual external learning on one hand, and the consequences of individual team members' external learning on team-level performance through the interpersonal interactions within teams on the other hand. To systematically investigate the proposed research model, I conducted three empirical studies to test the hypothetical relationships. In the preceding three chapters, I have described the details of each study. In this chapter, I further summarize the key findings from the three studies as well as discuss their key implications for theory and practice. I then reflect upon the limitations of the series of studies in this dissertation and end with recommendations for future research and an overall conclusion.

Summary of Key Findings

Given that I have reported the details of the findings from the three studies in the preceding chapters, here I simply summarize the results of each hypothesis testing in order to avoid redundancy. To facilitate interpretation, I have provided a summary of the results of the hypotheses testing along with the overall conceptual model that I presented in Chapter 1. From Figure 9 and Table 22, we can see that almost all the hypotheses were supported by the findings from at least one study, with H5a, H5b, H5c, H6a, H6b, and H6c being cross validated by Study 2 and Study 3. One exception was H9, which was not supported by any study. Overall, the findings from the three studies provided sufficient support for the proposed bottom-up model of the antecedents and consequences of individual external learning.

Table 22. Summary of Results of Hypotheses Testing

Hypotheses	**Study 1**	**Study 2**	**Study 3**
Hypothesis 1	Supported	—	—
Hypothesis 2	Supported	—	—
Hypothesis 3	Supported	—	—
Hypothesis 4	Supported	—	—
Hypothesis 5a	—	Supported	Supported
Hypothesis 5b	—	Supported	Supported
Hypothesis 5c	—	Supported	Supported
Hypothesis 6a	—	Supported	Supported
Hypothesis 6b	—	Supported	Supported
Hypothesis 6c	—	Supported	Supported
Hypothesis 7	—	Not supported	Supported
Hypothesis 8	—	Not supported	Supported
Hypothesis 9	—	—	Not supported
Hypothesis 10	—	—	Supported
Hypothesis 11	—	—	Supported

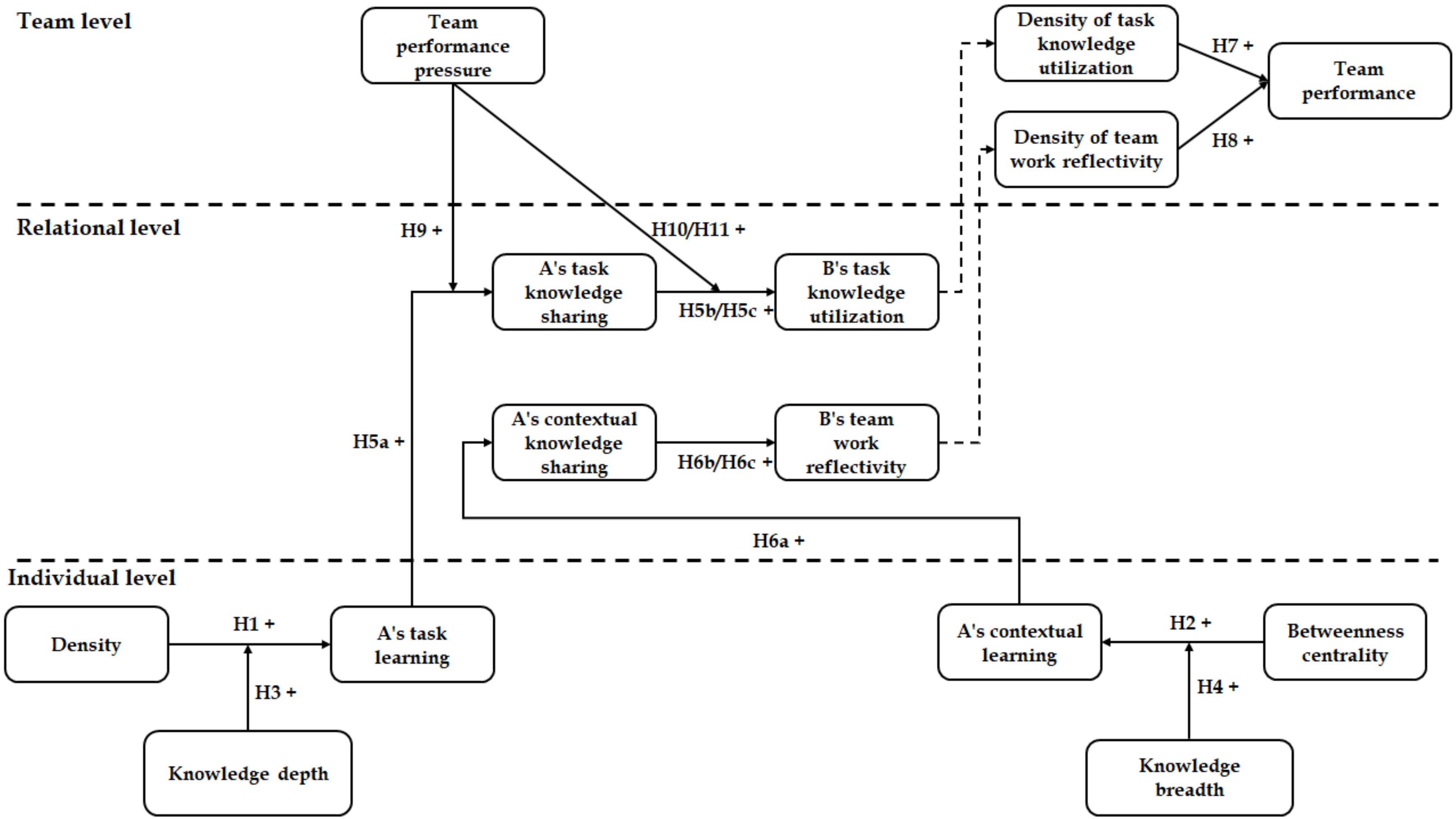

Figure 9. The overall conceptual model in the dissertation

Theoretical Implications

By proposing and testing the bottom-up model on the antecedents and consequences of individual external learning, I make several contributions to the current literature on external learning. First, I shift the unit of analysis downwards whereby external learning is conceptualized and operationalized from team level to an individual level to better align with the phenomenon in real workplaces. Although most of the studies in this research domain have conceptualized and operationalized external learning as team-level constructs with a referent-shift model (Chan, 1998), external learning behaviors are activities essentially undertaken by individual members on behalf of the team. Moreover, as Marrone (2010) notes, the individual behavioral contributions to team external learning may or may not be isomorphic or converge among members, but instead may vary in amount and type depending upon the characteristics of the team members as well the task and team interdependencies that exist among them. I corroborate this notion and shift the level downwards where external learning is conceptualized and operationalized, which makes the concepts better align with the phenomenon in real workplace.

Second, I advance the literature on external learning by highlighting the distinctions between task learning and contextual learning in terms of both their causes and effects. Though Bresman's (2010) seminal work conceptualized the two forms of external learning, it did not provide a theoretical account for the taxonomy of task versus contextual learning. By adopting the social network theory, I identified external network density as the antecedent of task learning while betweenness centrality was the predictor of contextual learning. In addition, by drawing on the team receptivity framework, I revealed that Member A's task learning was related to Member B's task knowledge utilization, whereas Member A's contextual learning was associated with Member B's team work reflexivity – both of which further contributed to team performance. As such, I advance the theoretical underpinnings of the classifications of external learning by demonstrating task learning is different from contextual learning in its antecedents as well as its consequences.

Third, the social network model on the antecedents of external learning also advances our understanding about why and when an individual engages in different forms of external learning. Though prior studies have identified psychological safety as a key driver for external learning (e.g., Bresman & Zellmer-Bruhn, 2013), I complement this with the motivational approach and also highlight the social structure in which an individual is embedded as important factors influencing individuals' opportunities to engage in different forms of external learning. Moreover, the introduction and identification of the characteristics of individuals' knowledge structures as new and important contingencies to the social network configurations–external learning relationships qualify social network theory as a useful perspective for untangling the different antecedents of distinctive external learning. My findings suggest that external network density, when complemented with knowledge depth, render it most likely that individuals will engage in task learning. Meanwhile, betweenness centrality in the external network, when coupled with knowledge breadth, will render it most likely that individuals will engage in contextual learning. Moreover, the interaction between the social network configurations and the characteristics of individuals' knowledge structures further highlight the distinctions between the two forms of external learning in terms of their antecedents.

Fourth, by drawing on the team receptivity framework and applying a bottom-up model, I provide a theoretical account of how and when the knowledge acquired through an individual team member's external learning is disseminated and integrated into team-level performance. In the literature on external learning and, more broadly, the literature on boundary spanning, it is assumed that such kinds of externally oriented activities are beneficial for team functioning and effectiveness, though scholars have admitted that limited theoretical or empirical work exists explaining how and when these positive outcomes should unfold (e.g., Marrone, 2010). I address this gap by first delineating the interactions occurring in the dyads between Member A who engages in external learning and knowledge sharing and Member B who exhibits receptive reactions towards Member A's behaviors and further link the relational-level interactions to team performance. As such, I advance the literature on external learning and boundary spanning by uncovering the previously assumed but seldom investigated knowledge dissemination and integration processes. Additionally, the findings that team performance pressure moderates the task learning–task knowledge utilization but not the contextual learning–team work reflexivity linkage also highlight the distinctions between the two forms of external learning in terms of their consequences.

In addition to the contributions to the literature on external learning, this dissertation also has several implications for the theoretical perspectives I have adopted in analyzing the antecedents and consequences of individual external learning. First, I contribute to the social network theory and literature in two ways. Specifically, I join an expanding body of literature which suggests that the realization of social network advantages is contingent upon individual characteristics (e.g., Anderson, 2008; Baer, 2010; Reinholt et al., 2011). Though traditional social network research has implicitly assumed the agency of individuals in taking purposeful actions, recent studies have claimed it is not automatic for individuals without sufficient agency to reap the benefits of social networks. I join this growing field of literature and identify the characteristics of individuals' knowledge structures as new and important individual attributes. The evidence I have presented and discussed, therefore, suggests a more nuanced understanding of individual agency in actualizing potential network advantages. Moreover, I also advance the complementary perspective of closure and brokerage. Prior literature has treated closure and brokerage as two ends of a continuum (e.g., Carnabuci & Diószegi, 2015). Recent studies have suggested that closure (e.g., density) and brokerage configurations (e.g., betweenness centrality) could exist simultaneously and produce complementary effects on knowledge and innovation management outcomes (e.g., Reagans & McEvily, 2008). I adopt this perspective and reveal that density and betweenness centrality could facilitate different forms of external learning, both of which would also contribute to team effectiveness. Therefore, instead of thinking in terms of trade-offs, the evidence I have provided suggests it may be more valuable to think in terms of the complementarity of the effects of these two network configurations.

Second, this dissertation also has threefold implications for the team receptivity framework. Primarily, by revealing task knowledge utilization and team work reflexivity as the mechanisms underlying the relationships between different forms of external learning and team performance, I highlight the substantial value of the team receptivity framework for understanding the effects of external learning. This advances matters because it suggests that this theoretical framework, which was originally developed to understand the effects of membership change and personnel movement, is also useful in explicating the phenomena associated with external learning. Moreover, in this dissertation, I distinguished task learning and the associated knowledge versus contextual learning and the associated knowledge, and further linked different forms of external learning to different receptive reactions. Echoing Kane and Rink (2017), this enriches the team receptivity framework by providing a more precise picture of the kinds of knowledge involved in the theoretical scope. Additionally, by adopting a multilevel analytical framework and the social relations model, I delineated the within-team microdynamics occurring between the members in dyads, which have also been called for by Rink and others (Kane & Rink, 2017; Rink et al., 2013). Lastly, the introduction and identification of team performance pressure as a new and important moderator also advances the team receptivity framework. Although previous studies in line with this framework have established team performance in prior periods as one of the most robust moderators, I depart from this established literature by shifting the focus from actual (poor) performance to expected (high) performance (i.e., team performance pressure). This departure extends our understanding of the boundary conditions of the team receptivity framework.

Practical Implications

Study 1 highlighted that individuals may employ different social structural routes to acquire information and knowledge outside of their team boundary. A dense external network and a position with high betweenness centrality within the external network are both important social network configurations that can be utilized for mobilizing knowledge-based resources outside of the team boundary. This opens the possibility for more team members to be involved in external learning since team members privileged in either dense advice networks or central advice positions can be encouraged to participate. Further, I also found that the knowledge depth and knowledge breadth of an individual could help the individual make more effective use of the information and knowledge available within the external network. This highlights for team members the value of the knowledge structure complementing the social structure in materializing the informational utilities that come with their position in the external network.

The findings from Study 2 and Study 3 generally demonstrate that task knowledge utilization and team work reflexivity are the key mechanisms through which task learning and contextual learning relate to team performance. Given this, I suggest that managers pay more attention to whether team members have disseminated and integrated knowledge related to the task in hand or the environment outside the team boundary. Moreover, managers can make use of team performance pressure to boost the motivation of the team members to utilize the shared knowledge. Because team performance pressure is a mix of high expectations and significant consequences, team managers could repeatedly convey the message to team members that they are expected to deliver superior performances and, consequently, the work outcomes should be scrutinized in a high-stakes manner. In so doing, team members will be motivated to adopt knowledge from the outside and to exhibit persistence during the knowledge transfer process.

Limitations and Future Directions

This dissertation has not been without its limitations. First, in Study 1 and Study 2, all the respondents were male since the research context was a power company, whose employees usually consist of males. However, as previous studies have revealed (e.g., Lanaj & Hollenbeck, 2015), the effects of individuals' cross-boundary activities may differ by gender because people have different expectations of men as opposed to women. As such, we should be cautious about whether the findings from these two studies can be generalized to organizations in which the gender of the employees is mixed or is 100% female.

Second, in Study 1 the correlation coefficients between task learning and contextual learning were relatively high. In Study 2 and Study 3, the six variables at relational level (i.e., task learning, contextual learning, task knowledge sharing, contextual knowledge sharing, task knowledge utilization, and team work reflexivity) were also highly correlated with each other. I speculate that this was due to the common-method variance. More specifically, the two variables in Study 1 were rated by team leaders, and the six variables in Study 2 and Study 3 were rated by peers with the round-robin method. The common rater effects and the workload to respond to the same question with different targets may have led to these high correlation coefficients (Podsakoff, MacKenzie, Lee, & Podsakoff, 2003). Nevertheless, as suggested by the results of the CFAs in each study, the hypothetical models fitted the data better than the alternative models when these constructs were combined. Therefore, I was able to capture distinct constructs to some extent. Even so, I suggest future research could re-explore the relationship with better measurement models, in which the correlation coefficients among the key constructs should be not so high.

Third, though in all three studies I tested the hypotheses with multi-wave and multi-source data, the conclusions were ultimately correlational. In particular, we should be cautious in interpreting the results from Study 2 and Study 3. Though my findings revealed that Member A's task learning was positively and indirectly associated with Member B's task knowledge utilization through Member A's task knowledge sharing, while Member A's contextual learning was positively and indirectly related to Member B's team work reflexivity through Member A's contextual knowledge sharing, I cannot rule out the possibility that the knowledge shared by Member A was not the total knowledge obtained from outside the team. To alleviate this concern associated with the causality, I emphasized that the knowledge was from the outside when measuring the two forms of knowledge sharing (e.g., "*[X] shares with me other teams' past failures and experiences that s/he obtained by discussing with others outside* [task knowledge sharing]" and "*[X] shares with me information on opportunities and threats that s/he obtained by scanning the environment beyond the team boundary* [contextual knowledge sharing]"). I suggest future research could utilize experimental methods to eliminate alternative explanations and draw definitive causal relationships between external learning, knowledge sharing, and receptive reactions.

Lastly, though I argued that density makes it possible for an individual to obtain similar task experience while betweenness centrality provides opportunities for an individual to access diverse information, I did not investigate these underlying mechanisms. I suggest future research could empirically address whether different network configurations do influence access to different information and, thus, promote different forms of external learning. Moreover, I identified knowledge depth and knowledge breadth as two moderators that may influence an individual's capacity to utilize the information available within the external network. However, prior studies have suggested individual differences such as need for cognition or openness to experience also act as contingencies (e.g., Anderson, 2008; Baer, 2010).

I suggest future research could explore these variables as the boundary conditions of the network configurations–external learning relationships. Correspondingly, in addition to the team-level contingencies, the team receptivity framework also highlights the characteristics of actor (i.e., Member B in my study), partner (i.e., Member A in my study), and dyadic relationships between actor and partner in moderating the microdynamics within teams (Rink et al., 2013). Indeed, I also explored the moderating role of the relevant variables that were treated as control variables in the current model (e.g., Member A and B's demographics, dyadic tenure, A's higher status than B, etc.), but no significant effects were revealed. I suggest future research could re-explore the moderating effects of these or other characteristics of the actor, partner, or dyad to obtain a more comprehensive understanding of the microdynamics I discovered in this dissertation.

Concluding Remarks

I began this dissertation by noting that both the antecedents and consequences of task versus contextual learning have not been well understood. The findings from this dissertation primarily suggest that task learning is different from contextual learning in both its causes and functions. Specifically, this dissertation reveals that the social network configurations in which an individual is embedded could interact with the characteristics of the individual's knowledge structure to jointly determine the different forms of external learning in which the individual may engage. Moreover, this dissertation further uncovered the previously assumed but seldom investigated processes linking individual team members' task versus contextual learning to team performance as well as identifying team performance pressure as a boundary condition that would strengthen the aforementioned processes. Taken together, these findings contribute to a better understanding of the antecedents and consequences of task versus contextual learning. I also hope to have provided managers with some practical implications with which they can better reap the benefits of their employees' external learning. If this dissertation is regarded as a good starting point for studies that intend to examine the causes and effects of task versus contextual learning and further stimulates future research and practice, then all the effort involved in its production will have been worth it.

APPENDICES

Appendix 1 Scales used in Study 1 (Chinese version)

Need for cognition

1. 我在思考中获得快乐
2. 我喜欢处理需要深思熟虑的复杂问题
3. 完成需要新思路才能解决的任务对我来说是一种享受

Proactive personality

1. 不管可能性多大，我会努力达成我所认定的事
2. 我通常会坚持自己的想法，即使它和其他人的意见相左
3. 在工作和生活中，我善于发现机会
4. 没有什么能阻碍我去实现我认定的想法

Task learning

1. 他从团队外搜集信息以了解谁能给我们团队任务上的指导或帮助
2. 他试图了解其他团队的工作并希望从中获得我们团队可借鉴的经验教训
3. 他邀请团队外的人到我们团队一起讨论如何避免再犯他人已经犯过的错误
4. 他与团队外的人讨论他们失败的经历，以获得改进我们团队工作的方法
5. 他与团队外的人回顾他们成功的经验，以获得我们团队开展类似工作的方法

Contextual learning

1. 他关注了解公司和处室领导对于我们团队的最新指示与要求，确保我们的工作正确合理

2. 他向团队外相关方询问完成我们团队任务所需材料、工具的最新信息，确保我们的工作准确无误

3. 他向团队外相关方询问交付我们团队工作的时间、地点的最新信息，确保衔接流畅

4. 他向团队外相关方咨询当前机组运行采用的最新技术标准和参数，确保我们团队的操作安全合规

5. 他打听了解那些执行类似任务的处室或团队的最新工作情况，确保我们团队的工作质量不落后于人

Appendix 2 Scales used in Study 2 (Chinese version)

Social status

1. 他在我们团队很受尊重

2. 他在我们团队中做出了很有价值的贡献

3. 他对团队决策的影响很大

A's task learning

1. 他从团队外搜集信息以了解谁能给我们团队任务上的指导或帮助

2. 他观察其他团队的工作并希望从中获得我们团队可借鉴的经验教训

3. 他与团队外的人讨论成功的经验或失败的教训，以获得我们团队开展类似工作的方法

A's contextual learning

1. 他关注了解公司和处室领导对于我们团队的指示与要求，确保我们的工作正确合理

2. 他向团队外相关方咨询当前机组运行采用的技术标准和参数，确保我们团队的操作安全合规

3. 他向团队外相关方询问完成我们团队任务所需的资源以及交付工作的时间等信息，确保工作准确无误、衔接流畅

A's task knowledge sharing

1. 他把从团队外获得的、有关谁能帮助我们团队完成任务的信息分享给我

2. 他把从观察其他团队工作中获得的、可供我们团队借鉴的经验教训分享给我

3. 他把从和团队外的人讨论中获得的、我们团队工作可以借鉴的方法分享给我

A’s contextual knowledge sharing

1. 他把从团队外获得的、公司和处室领导对于我们团队的指示与要求分享给我

2. 他把从团队外获得的、当前机组运行采用的技术标准和参数分享给我

3. 他把从团队外获得的、有关我们团队工作所需资源以及交付工作的时间等信息分享给我

B’s task knowledge utilization

1. 我尝试了他推荐的工作方法

2. 我采用了他建议的工作步骤

3. 我采纳了他提供的工作建议

B’s team work reflexivity

1. 在与他的互动中，我回顾反思了工作的目标和方法

2. 经过与他的互动，我调整了工作的目标和方法以适应新的情况

3. 在和他互动时，我很容易产生以前从未有过的想法

External task similarity

1. 我们团队与处室内其他团队在工作所需的方法、知识和技能等方面相似

External interdependence

1. 为了完成工作，我们团队必须要与其他团队交换信息和意见
2. 为了妥善完成任务，我们团队必须要与其他团队紧密合作
3. 我们团队经常需要和其他团队一起合作检查工作进展

Team shared goal

1. 我们团队的成员在工作中荣辱与共
2. 我们团队的成员在工作上目标一致
3. 所有团队成员总是寻求相同的目标
4. 我们团队的所有成员彼此间都很熟悉

Team performance

1. 我们团队的工作效率很好
2. 我们团队的工作质量很高
3. 我们团队的总体工作表现很好

Appendix 3 Scales used in Study 3 (Chinese version)

Social status

1. 他在我们团队很受尊重

2. 他在我们团队中做出了很有价值的贡献

3. 他对团队决策的影响很大

A's task learning

1. 他/她从团队外搜集信息以了解谁能给我们团队任务上的指导或帮助

2. 他/她观察其他团队的工作并希望从中获得我们团队可借鉴的经验教训

3. 他/她与团队外的人讨论成功的经验或失败的教训，以获得我们团队开展类似工作的方法

A's contextual learning

1. 他/她关注了解公司领导和其他团队对于我们团队工作的要求或需求，确保我们的工作正确合理

2. 他/她打听了解有关客户、竞争对手的技术及市场趋势信息，确保我们团队的工作具有优势

3. 他/她关注学习宏观经济、法律和政策信息，确保我们团队的工作合理合规

A's task knowledge sharing

1. 他/她把从团队外获得的、有关谁能帮助我们团队完成任务的信息分享给我

2. 他/她把从观察其他/她团队工作中获得的、可供我们团队借鉴的经验教训分享给我

3. 他/她把从和团队外的人讨论中获得的、我们团队工作可以借鉴的方法分享给我

A's contextual knowledge sharing

1. 他/她把从团队外获得的、公司领导和其他团队对于我们团队工作的要求或需求分享给我

2. 他/她把从团队外获得的，有关客户、竞争对手的技术及市场趋势信息分享给我

3. 他/她把从团队外获得的，有关宏观经济、法律、政策及公司内部制度的信息分享给我

B's task knowledge utilization

1. 我尝试了他推荐的工作方法

2. 我采用了他建议的工作步骤

3. 我采纳了他提供的工作建议

B's team work reflexivity

1. 在与他的互动中，我回顾反思了工作的目标和方法

2. 经过与他的互动，我调整了工作的目标和方法以适应新的情况

3. 在和他互动时，我很容易产生以前从未有过的想法

External task similarity

1. 我们团队与处室内其他团队在工作所需的方法、知识和技能等方面相似

External interdependence

1. 为了完成工作，我们团队必须要与其他团队交换信息和意见

2. 为了妥善完成任务，我们团队必须要与其他团队紧密合作

3. 我们团队经常需要和其他团队一起合作检查工作进展

Team shared goal

1. 我们团队的成员在工作中荣辱与共

2. 我们团队的成员在工作上目标一致

3. 所有团队成员总是寻求相同的目标

4. 我们团队的所有成员彼此间都很熟悉

Team performance pressure

1. 我们团队的绩效压力很大

2. 我们都觉得要实现预期的绩效目标有很大的压力

3. 如果不能有良好的团队绩效，我们的“饭碗”将不保

4. 我们团队所处的氛围可以说是高度结果导向的

Team performance

1. 我们团队的工作效率很好

2. 我们团队的工作质量很高

3. 我们团队的总体工作表现很好

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