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Understanding the Impact of Emergent Conflict on Communication and Team Cognition: A Multilevel Study in Engineering Teams

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UNDERSTANDING THE IMPACT OF EMERGENT CONFLICT ON COMMUNICATION AND TEAM COGNITION: A MULTILEVEL STUDY IN ENGINEERING TEAMS

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ABSTRACT

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The development of team cognition is crucial for fostering high-performing teams. In cognitive-intensive fields like engineering, effective communication serves as a primary precursor to team knowledge development, enabling group members to effectively retrieve and utilize each other's expertise. Despite the critical role of communication, there is a lack of empirical research examining how conflict situations, which are critical emerging factors inherent to teamwork, interact with communication processes to constrain team knowledge development and utilization. This study, rooted in information processing theory, investigates how emerging conflict shapes multilevel team knowledge structures by interacting with communication processes in engineering project teams. Prior approaches focused on the team level of analysis fail to capture the natural variability in team interactions that occur at lower levels. The proposed mathematical approach examines dyadic structures within teams as the building blocks by employing multivariate matrices to capture the variables of interest for each dyad within a team. Findings indicated that certain conflict profiles interacted with intragroup communication to affect the effective use of transactive memory systems. Affective conflict combined with high levels of task-related disagreements is most dysfunctional to teams but less so when members share similar perspectives about task execution. This research sheds light on how naturally arising cognitive and affective conflicts impact knowledge-based processes. These results can inform evidence-based interventions to prevent and mitigate dysfunctional conflict

and improve knowledge retrieval. Additionally, it offers new insights into team communication and cognition by presenting a mathematical matrix-based framework to examine teams at the dyadic level.

This dissertation is dedicated to the proposition that the harder you work, the luckier you get.

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NOMENCLATURE

TMS	Transactive Memory Systems
ICC	Intraclass Correlation Coefficient
$E\rho^2$	Generalizability Coefficient of Reliability
r_{wg}	Within-group interrater agreement coefficient
MCFA	Multilevel Confirmatory Factor Analysis
REML	Restricted Maximum-Likelihood estimation
χ^2	Chi-squared
CFI	Comparative Fit Index
RMSEA	Root Mean Square Error of Approximation
SRMR	Standardized Root Mean Square Residual

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CHAPTER 1

INTRODUCTION

1.1 BACKGROUND

There is broad consensus from the literature suggesting that the development of transactive memory systems reflecting the knowledge structure in a team facilitates the effective integration of information and knowledge among members and stimulates team effectiveness. Research has also shown that a failure to share and integrate various cognitive resources in a team can prevent their success (Maynard et al., 2019). The nature of within-team interactions plays an essential role in an individual's decisions to share information and knowledge when working in teams, thereby affecting the team's ability to accomplish cognitively demanding tasks (Su, 2021). Examining how a team's critical processes, such as communication and cognition, are affected by emerging factors inherent to group collaboration is essential to understanding effective teamwork.

Successful teamwork relies on effectively using the team's cognitive resources to accomplish their goals. Nevertheless, cognitive and affective conflicts are likely to emerge due to members' interactions because their perspectives and ideas may be divergent (Todorova, 2020). Conflict can challenge individuals' interactions and increase their cognitive load, constraining the teams' ability to process information effectively (Bradley et al., 2015). Cognitive and affective conflicts may have different implications for team cognition because of the type of disagreements they emerge from. Examining the relationships between different facets of intra-team conflict and team cognition is critical to building high-performing team-based systems. The proposed study will contribute to the literature by investigating what facets of intrateam conflict enhance or inhibit communication and team cognition in engineering teams.

A transactive memory system is commonly used to represent team cognition (Bachrach et al., 2019) as a shared system formed by individuals' beliefs about the knowledge possessed by another and the set of transactive processes among group members to cooperatively store, encode, and retrieve information (Hollingshead, 2001; Lewis, 2004; Palazzolo, 2017). Past studies uniformly support the critical role of transactive memory systems in achieving sustainable performance and learning (Bachrach et al., 2019; DeRue & Sytch, 2019) by allowing teams to achieve higher levels of collective learning, trust, satisfaction, and creativity (Hollingshead, 2001; Zhou & Pazos, 2020). Teams executing interdependent, externally driven, and specialized time-constrained tasks, such as project teams, are most likely to benefit from the different perspectives, know-how, and ideas their members possess (Kozslowski & Bell, 2013). Therefore, understanding what drives the development and operation of transactive memory systems can help us build more effective project teams.

Existing studies have identified several key drivers of teams' transactive memory systems. Some of these factors mainly influence team members' interactions, such as task incentives (Hollingshead, 2001), role identification behaviors (Pearsall et al., 2010), team-skills training (Prichard & Ashleigh, 2007), team member familiarity (Lewis, 2004), task interdependence, cooperative goal interdependence, or support for innovation (Zhang et al., 2007). Other factors relate to the processes that support the execution of the task such as communication volume and frequency (Jackson & Moreland, 2009; Lewis, 2004; Peltokorpi & Manka, 2008). Despite the critical role of communication, there is a lack of empirical research examining how emerging factors influence intrateam communication and transactive memory systems in knowledge-intensive teams.

A literature review revealed that only a handful of studies have examined the relationship between different intrateam conflict types and transactive memory systems (e.g., Bachrach et al., 2014; Rau, 2005; Todorova, 2020). Likewise, fewer studies have examined the factors that simultaneously influence transactive memory systems at multiple levels (e.g., Yuan, Fulk, et al., 2010). The scarce information regarding how intrateam conflict affects the development of transactive memory systems has been discussed in recent studies (Peltokorpi & Hood, 2019; Yan et al., 2021). Accordingly, this study identified three main research opportunities.

First, previous studies mainly investigated how conflict moderates or mediates the transactive memory systems - performance outcomes association (e.g., Bachrach et al., 2014; Rau, 2005; Riley & Ellegood, 2019). Conversely, this research proposed to look at intrateam conflict as a precursor of transactive memory systems by studying how it interacted with intrateam communication to influence the development of team cognition. This view was in line with the work of Gibson (2001) and Staw et al. (1981), who noted that different types of intrateam conflict affect information processing by disrupting individuals' interactions, including communication patterns and information exchange.

Second, although the original theory proposed by Wegner (1987) identified two essential components of transactive memory systems, an organized form of knowledge and a set of transactive processes to maintain the memory structure (Hollingshead, 2001; Ren & Argote, 2011; Wegner, 1987), most studies often focus on only one of these elements (Pearsall, 2008). While the memory structure can be understood as a group-level manifestation, the transactive processes can be captured as representations of members' interactions to exchange information and knowledge. Together, these two theoretical components illustrate a collective memory where individuals know who knows what, which allows them to rely on one another to retrieve specific information and knowledge (Wegner, 1987). A prevalent call exists in the literature to study the factors that shape teams' transactive memory systems at multiple levels, including individual, dyadic, and group-levels (Barnier et al., 2018; Kush, 2019; Wagner, 2014).

Third, research investigating team processes and emergent states has mainly adopted aggregation approaches to describe group-level constructs (Murase et al., 2012) while relying on the assumption of individual and relational homogeneity (Humphrey & Aime, 2014; Marineau et al., 2018). Through this approach, a group-level construct is often estimated using parameters of central distribution (mean or median) or dispersion (i.e., std. deviation) that may not capture their emergence from team members' patterns of knowledge-based interactions. Many team-level constructs exhibit characteristics that cannot be captured through these compositional methods because team members might relate, interact, and organize with other individuals differently at the dyadic level (Crawford & LePine, 2013; Park, Grosser, et al., 2020). Intrateam conflict (Park, Mathieu, et al., 2020), communication (Su, 2021), and transactive processes (Yuan, Carboni, et al., 2010) are relational variables that are subject to dyadic differences based on the specific interaction between members. Thus, it becomes essential to adopt more sensitive approaches, such as network analysis, to account for different relational configurations through which these team constructs emerge (Humphrey & Aime, 2014; Humphrey et al., 2017; Park, Grosser, et al., 2020; Yang et al., 2019).

In sum, the present study aimed to approach three research opportunities. It focused on the interplay between intrateam conflict types and communication in predicting transactive memory systems' operation. These relationships were examined at the dyadic and group levels, adopting a two-level perspective. A relational view grounded on network theory was adopted to characterize the emergence of group-level constructs from dyadic interactions.

1.2 PROBLEM IDENTIFICATION AND RESEARCH QUESTIONS

Although increasing attention has been paid to the enablers and barriers of transactive memory systems, only a handful of studies have examined the role of different types of intrateam conflict (e.g., Bachrach et al., 2014; Rau, 2005; Todorova, 2020). Moreover, fewer studies have discussed the factors that simultaneously influence the components of transactive memory systems at different levels (e.g., Yuan, Fulk, et al., 2010). In response, the proposed study approached these gaps in the context of engineering project teams. The information processing theory was used as a framework, and a social network lens was adopted to capture the relational nature of the variables under study. The following research questions guided the study:

1. How does intrateam communication relate to transactive memory systems at the dyadic and group levels?
2. Does the relationship between intrateam communication and transactive memory systems at the dyadic and group level vary based on cognitive conflict? If so, how?
3. Does affective conflict interact with cognitive conflict in shaping the relationship between intrateam communication and transactive memory systems at the dyadic and group levels? If so, how?

Addressing these research questions was expected to enhance our understanding about the relationships between communication networks and transactive memory systems and the moderation role of cognitive and affective conflicts. There is evidence of the potential benefits of developing these systems, so investigating how different patterns of conflict and communication may facilitate or disrupt its functioning is relevant to building effective project teams.

1.3 RESEARCH PURPOSE

Different types of disagreements emerge in teams due to team members' interactions during project execution. Understanding the influence of intra-team conflict on intrateam communication and teams' transactive memory systems is critical to optimizing team functioning and cognition. The proposed study aimed to contribute to the engineering management body of knowledge by examining a theoretical model that related intrateam communication to transactive memory systems, having two types of intrateam conflict that captured the team's cognitive and affective disagreements as moderators in this relationship using a sample of engineering project teams.

Intrateam conflict was seen as a mechanism that interacts with communication by allowing or preventing groups from integrating their cognitive resources, which is critical to developing the team's transactive memory system. The research hypotheses about the relationships among these variables at the dyadic and group levels were built upon the information processing theory and existing literature. Communication was defined in terms of the perceived quality of interactions to exchange information between individuals. Intrateam conflict was defined as the team members' perceptions of disagreements regarding values, ideas, and preferences, which can be cognitive or affective. A transactive memory system was described as a shared system formed by individuals' beliefs about the knowledge possessed by another and the set of transactive processes to store, encode, and retrieve information from others cooperatively.

The proposed research hypotheses were tested using data collected from a sample of project teams using previously developed measurement scales. Statistical tools were used to analyze the data and test the hypotheses.

1.4 DEFINITION OF VARIABLES

The variables under study are defined based on existing literature (e.g., Jehn et al., 2013; Lewis, 2003; Park, Mathieu, et al., 2020; Yuan, Carboni, et al., 2010; Yuan, Fulk, et al., 2010). A detailed discussion about conceptualizing these variables is presented in Chapter 2.

Table 1.

Definition of variables

Concept	Variable	Level	Definition
Intrateam communication	Communication quality	Dyadic	Perceived communication quality between two team members.
	Communication quality density	Group	Communication quality within a team resulting from the perceived communication quality across dyads.
Intrateam conflict	Cognitive conflict	Dyadic	Degree to which differences due to divergent ideas and viewpoints related to the task's content and outcomes are perceived between two team members.
	Cognitive conflict density	Group	Degree of perceived differences due to divergent ideas and viewpoints related to the task's content and outcomes within a team.
	Affective conflict	Dyadic	Degree to which interpersonal incompatibilities and emotional tensions are perceived between two team members.
	Affective conflict density	Group	Degree of perceived interpersonal incompatibilities and emotional tensions within a team.
Transactive memory systems	Expertise retrieval	Dyadic	Perceived frequency to which information and knowledge are retrieved between two team members.
	TMS use	Group	The extent to which a team operates their cognitive structure as manifested by their level of expertise awareness, task credibility, and task coordination.

1.5 THEORETICAL FRAMEWORK

The proposed study investigates how communication and intrateam conflict interact and relate to transactive memory systems. The research model is grounded on the information processing theory and informed by the structural and relational underpinnings of social network theory. The information processing framework provides a substantial background for understanding different processes related to collective cognition (Hinsz et al., 1997). Inspired by the computer systems' metaphor, the information processing theory builds on cognitive psychology's foundations to research small-world systems (Arrow et al., 2000). The information processing perspective describes how groups collect, exchange, share, and process information (Gibson, 2001; Lee, 2014) while emphasizing the pivotal role of these processes for individual and group-level outcomes (Brauner & Scholl, 2000; Hinsz et al., 1997).

The approach of groups as “systems for organizing and processing information” (Arrow et al., 2000, p. 19) acknowledges two relevant properties for the present study. First, under this perspective, teams generate better outcomes than individuals working alone. For this to happen, members must share their capabilities and information to access a full range of skills and knowledge necessary to perform interdependent tasks as part of a project team. Second, it acknowledges the team cognition’s emergence and structural properties originate from team members' interactions to share ideas, resources, information, etc. (Humphrey & Aime, 2014). It also considers that the sharing of resources occurring at multiple team levels is interdependent, implying that individual-level processing affects group-level processing and vice versa (Hinsz et al., 1997).

The information processing framework applied to small-group research has a long history, which can be traced back to the 1950s (Brauner & Scholl, 2000). Diverse social behavior studies show that the propositions of the information processing theory remain active. The principles and foundations of information processing theory have been adopted in the study of shared mental models (Ellis, 2006), transactive memory in groups (Brandon & Hollingshead, 2004; Hollingshead, 1998; Wegner, 1987), group decision making (De Wit et al., 2013; McLeod, 2013), information exchange, and creativity (Dennis, 1996; Gong et al., 2013).

There are different information-processing models in the literature on management and cognitive psychology. Lord and Maher (1990) identified four information processing models that characterize most research in these areas: rational, limited capacity, expert, and cybernetic models. Despite various models, they share core elements to explain information processing. The present study builds on the general theoretical framework proposed by Gibson (2001), which describes four phases that characterize group cognition: accumulation, interaction, examination, and information accommodation.

The abovementioned phases are described as follows. Accumulation occurs through the acquisition of new information. This information is disseminated within the process of interaction among members. In the examination phase, members work together to interpret and evaluate the information, which is later used to make decisions and generate actions within the accommodation phase. Transitions from one stage to another are not always linear; sometimes these phases follow reciprocal relationships and reverse cycles. Indeed, permutations of the sequence among phases are delineated by specific catalysts acting as dual forces that must be balanced in a group. Conflict is a catalyst that influences interaction activities, including communication patterns and exchange of information, and examination subprocesses, such as interpretation and evaluation (Gibson, 2001). The current study relies on this theoretical perspective to integrate intrateam conflict as a factor that interferes with teams' information processing.

The information processing perspective also acknowledges that group cognitive processes emerge and develop through individuals' interactions (Humphrey & Aime, 2014). As Gibson (2001) described, cognitive processes result from patterns of connections and interrelations between group members. This relational view of group cognition is also a core proposition in the social network theory. This theory recognizes that individuals are embedded in networks where they interact and relate to other social entities. The patterns of interactions and relationships shape the structural characteristics of the network and have significant implications on individuals' behaviors or actions and vice versa (Sarker et al., 2011). These interactions also affect how information and knowledge are acquired, processed, and utilized. Furthermore, the network's patterns of relationships and structural characteristics can affect individual, dyadic, and group-level outcomes (Scott & Carrington, 2011; Wasserman & Faust, 1994). Hence, the social network approach informs the relational characterization of teams' intrateam communication, conflict, and transactive processes.

1.6 SIGNIFICANCE OF THE STUDY

The significance of this study is noticeable as it contributes valuable insights into the management of engineering teams in various ways. This study addresses current calls to investigate how different facets of conflict affect communication networks and the effective use of team cognition (Peltokorpi & Hood, 2019; Yan et al., 2021). By focusing on engineering project teams, the study findings could help engineering managers understand how team cognition is affected by naturally emergent cognitive and affective conflicts and develop appropriate interventions to facilitate team functioning. The outcomes of this study might contribute to our theoretical understanding of the implications of the intrateam conflict for team cognition by focusing on its dyadic emergence. While most research on intrateam conflict has focused on its group-level characterization, its relational emergence must be addressed. Recently, scholars have argued that the dyad component should be placed at the center of the intrateam conflict conceptualization because teams are built from these dyadic interactions (Humphrey et al., 2017). Adopting improved methods enhances the study's significance as it addresses permanent calls to consider the multilevel "organizing" nature of team-level constructs (Humphrey & Aime, 2014) that the traditional aggregation methods overlook.

1.7 ORGANIZATION OF CHAPTERS

The research study is organized into five chapters. Chapter 1 includes a background of the study, describes the problem and research questions, states the purpose of the study, presents the theoretical framework, and includes the expected contributions and limitations. The remaining chapters are organized as follows. Chapter 2 reviews the literature on communication in teams, intrateam cognitive and affective conflict, and teams' transactive memory systems. This section concludes by discussing the research model and the proposed hypotheses. Chapter 3 presents the methodology adopted in this study. It describes the selection of participants, the instrumentation, and the data collection and analysis procedures. Chapter 4 presents the study results. It includes the sample demographics, descriptive information of the study variables, and results of the hypotheses testing. Chapter 5 is dedicated to discussing the study findings, including implications for theory and practice, recommendations for future research, and conclusions.

CHAPTER 2

BACKGROUND OF THE STUDY

2.1 INTRODUCTION

This chapter reviews the literature pertinent to the research study, which includes intrateam communication, emergent conflict, transactive memory systems in teams, and the relevance of these variables for team effectiveness. The literature review focuses on describing the variables related to the research problem, the status of the literature, and discussing the existing gaps in support of the study purpose. The last section of the chapter conveys the current literature supporting the proposed relationships between the study variables.

2.2 INTRATEAM COMMUNICATION

Communication is often defined as a behavioral process through which individuals exchange information (Johnson & Lederer, 2005). Such exchange can occur through different channels (i.e., interpersonal, computer-mediated, email), between two or more individuals, and it can vary in frequency (Marlow et al., 2018), structure, and openness of the information exchange (Hoegl & Gemuenden, 2001). The literature also suggests that communication can be characterized by the content of the information being exchanged. For instance, it can be task-oriented when the content is related to work or relational-oriented when the purpose is social rather than functional (Liao et al., 2012; Yan et al., 2021). Communication is fundamental in teams because it sets the foundation for other critical teamwork processes that enable task completion (Bradley et al., 2013).

Among the different aspects characterizing intrateam communication, this study considered three critical elements of its quality: frequency, openness, and directness.

Communication frequency concerns the amount of interaction to exchange information (Smith et al., 1994). Open communication indicates how information and opinions are freely and openly exchanged (Chun & Choi, 2014). Direct communication reflects the absence of intermediaries in the communication process between two individuals (Hoegl & Gemuenden, 2001). These three attributes indicate that the information is disclosed openly with sufficient frequency and through the shortest path possible, facilitating a high-quality communication process.

Past studies on intrateam communication generally capture the frequency with which team members interact with others to exchange information (Marlow et al., 2018; Neumeyer & Santos, 2020). Existing evidence suggests that pairs of members who communicate frequently are more likely to seek information during taskwork than those with less frequent communication (Yuan, Carboni, et al., 2010). Furthermore, research has shown that frequent interactions allow members to build trust in one another (Yan et al., 2021) and develop implicit and explicit coordination (Reimer et al., 2017).

Other studies have supported the relevance of open and direct communication within teams. Open communication allows members to access relevant information (Hoegl & Gemuenden, 2001) and helps them recognize what others want regarding the group work (Chun & Choi, 2014). Direct communication helps to reduce the effort needed to access information, which translates into better coordination and information flow across the team (Hoegl & Gemuenden, 2001). Conversely, it has been noted that a lack of direct and open communication overutilizes members’ time, leads to faulty transmissions, and hinders information relevant to task execution (Chun & Choi, 2014; Hoegl & Gemuenden, 2001).

The literature on intrateam communication supports its relevance for information transmission, learning (Badke-Schaub et al., 2010), and teamwork (Reimer et al., 2017).

Building from this evidence, it is presumed that the more frequent, open, and direct the intrateam communication takes place, the better team members coordinate, understand each other skills and knowledge, and overall, perform their taskwork effectively (Peltokorpi & Manka, 2008).

2.2.1 Communication and team performance

Communication is considered a critical process in teams (González-Romá & Hernández, 2014). Through communication, team members share relevant information, provide, and receive feedback, and solve problems effectively. Research has shown that team communication is a driver of effective teamwork (Salas et al., 2005) through facilitating information flow and coordinated action (Reimer et al., 2017). Conversely, a lack of communication leads to misunderstandings about tasks, goals, roles, and detriments coordination (Reimer et al., 2017).

Research investigating its role in achieving high performance considers communication to facilitate more proximal factors such as coordination and cooperation. Kozlowski and Bell (2003) and Kozlowski and Ilgen (2006) argued that communication is integral to group behavior because it enables other primary processes that aid taskwork and teamwork. Communication is critical for several transition, action, and interpersonal team processes (Bradley et al., 2013) that characterize team effectiveness. Likewise, communication can support the development of team solutions to problems during task execution and facilitate productive interactions among members that enhance the quality of outcomes (Kozlowski & Ilgen, 2006). Other empirical studies suggest that increased communication levels among team members are likely to benefit team performance by improving team cohesion (Patrashkova-Volzdoska et al., 2003) and creating conduits for expertise exchange (Hollingshead, 1998).

A meta-analysis conducted by Marlow et al. (2018) uncovered some of the primary functions of team communication. These authors noted that communication supports distributing crucial information besides clarifying misunderstandings among team members. This function is also relevant for disseminating information about the environment or situational factors that may affect the nature of the work. Furthermore, communication can lead to cognitive team states, which are argued to foster team performance through facilitating knowledge integration. The meta-analysis of 150 independent studies revealed that communication is positively related to team performance. This association is similar at different levels of task interdependence and task type (cognitive vs. action-based).

Research has also investigated whether the positive relationship between communication and performance is sustained at the individual level. Zhang and Huai (2016) conducted one cross-sectional (127 groups and 479 individuals) and one longitudinal study (104 groups and 397 individuals) to test a series of hypotheses, including the positive relationship between individuals' communication ties and individuals' tasks and creative performance. Because individual observations were nested in groups, hierarchical linear models were used for hypothesis testing. Results were consistent across studies supporting that the number of communication ties predicts both performance types. These findings prove that communication benefits can translate from the individual level to the team level and vice versa.

2.2.2 Communication networks

The network perspective is a promising grasp to conceptualize and analyze the structure and patterns of communication processes in groups and organizations. This approach has gained popularity among scholars over the past decade (e.g., Argote et al., 2018; Neumeyer & Santos, 2020; Susskind & Odom-Reed, 2019; Yan et al., 2021; Yuan, Fulk, et al., 2010). Conceptualizing intrateam communication as a network allows mapping relational structures and exploring the determinants and consequences of these structures at different network levels. According to the network view, a communication network displays the relationships among group members resulting from the extent to which they communicate. These communication patterns can be represented by different structural measures commonly used in network analysis (Kush, 2016).

From the social network perspective, several indicators can characterize communication networks. Wasserman and Faust (1994) proposed a classification of these metrics based on the level of analysis: actor/individual role, a subset of actors, and entire groups. The first category includes measures to study individuals, their position, and their patterns of connections with others, such as degree centrality. The second category involves the description of the subgroups such as dyads and triads and positional analysis. The third classification focuses on the overall network connectedness and group composition. Measures at this level include network size, density, and centralization. Centrality and density are the metrics most commonly used when investigating groups' networks (Brass & Borgatti, 2020).

Their degree of centrality represents a team member's relative position in the communication network. Degree centrality indicates with whom a member communicates directly in the network and to what extent (Su, 2012). Following the principles of the network theory, a high degree of centrality in the communication network suggests that a member has direct and frequent communication with every other member, making this member active and central in the group (Scott & Carrington, 2011). Therefore, team members with a high degree of centrality are presumed to have a more significant advantage in accessing information and learning what others know than members with a low degree of centrality (Brandon & Hollingshead, 2004; Su, 2012),

Communication network density indicates the amount of communication across the team (Peltokorpi & Hood, 2019). Following the terminology used in network theory for valued data, communication network density indicates the degree of communication among team members as a proportion of the possible communication ties between all pairs. Thus, a dense and fully connected network suggests that all members share the same communication pathways as their teammates (Argote et al., 2018). Prior studies indicate that high-density levels in the communication network facilitate information flow (Argote et al., 2018), expertise awareness, and subsequent information retrieval and allocation (Kush, 2016; Peltokorpi & Hood, 2019).

Although studies on teams or organizational communication networks have mainly used individual and group-level measures, the possibility of measuring actor-by-actor patterns of interactions makes network analysis a promising approach to investigating the implications of dyadic communication (Su, 2021). Because a network lens focuses on relational ties, it can capture potential differences in dyadic-level interactions that cannot be identified with other individual or group-level measures (Yuan, Carboni, et al., 2010). In past years, scholars have promoted the study of dyadic interactions, arguing that these relations are the essential components of teamwork that bring teams into existence (Humphrey et al., 2017).

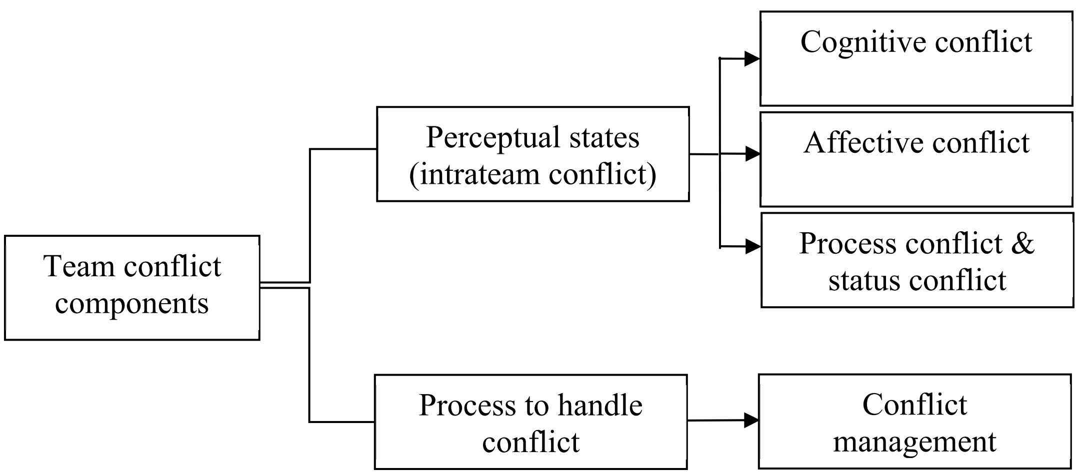
The literature shows that intrateam communication is positively associated with team performance. On the other hand, conceptualizing communication as a network allows for investigating its multilevel structural characteristics, antecedents, and consequences. Patterns of dyadic communication and communication density can help to understand the relational structures of this critical team process.

2.3 INTRATEAM CONFLICT

Prior research often characterizes team conflict as a process. However, this view lacks differentiation between two different conflict components: the perceptual state of disagreements and the process of handling such disputes (De Dreu, 2006). In addressing this distinction, DeChurch et al. (2013) proposed separation between conflict states, defined as the members' perceptions about the intensity of task-related or interpersonal disagreements, and conflict management, referred to as the strategies employed to manage disputes and related consequences (Figure 1). This research focuses on conflict states, referred to as intrateam conflict, in this document for simplicity. The relevant literature on intrateam conflict is presented next.

Figure 1.

A distinction between components of team conflict



2.3.1. Types of intrateam conflict

The influence of intrateam conflict on group outcomes, whether functional or dysfunctional, has been examined over the years across disciplines (O'Neill & Mclarnon, 2018;

Wall Jr & Nolan, 1986; Wiiteman, 1991). As the attention on the effect of intrateam conflict on team effectiveness increased over the years, the focus evolved into differentiating forms of conflict that might be beneficial for team performance from those considered detrimental (Amason & Schweiger, 1994; Amason et al., 1995; Jehn, 1994; Sessa, 1994). An essential contribution to this discussion was the separation between cognitive conflict and affective conflict, which are theorized to have different effects on performance (Brykman & O'Neill, 2021; De Wit et al., 2012; Jehn, 1994; O'Neill & Mclarnon, 2018).

Intrateam conflict refers to disagreements between team members regarding their perceptions of values, ideas, and preferences (Jehn, 1995). Intrateam conflict has two primary facets: cognitive (or task conflict) conflict, which relates to differences due to divergent ideas and viewpoints related to the task's content and outcomes; and affective conflict (or relationship conflict), which involves interpersonal or emotional tensions among group members (Humphrey et al., 2017; Jehn, 1995). In the past decade, scholars recognized two additional types of intrateam conflict: process and status conflict. Process conflict is the perceived disagreements about resource allocation and role assignments to approach the tasks (i.e., workload distribution, logistics) (Behfar et al., 2011; O'Neill et al., 2013). Status conflict relates to disputes over members' relative social standing in their group's social hierarchy (Bendersky & Hays, 2012; Bradley et al., 2015). Past research has mainly focused on cognitive and affective conflict, while the literature on process and status conflict is limited (Todorova, 2020).

The work conducted by Jehn (1994) contributed significantly to the study of different facets of intrateam conflict. She completed a series of studies in the 1990s that formalized the distinction between conflict states and developed a measurement scale to examine cognitive and affective conflict (De Dreu & Weingart, 2003). The work of Behfar et al. (2011) provided another essential contribution to the literature by refining a measurement instrument that includes, besides cognitive and affective conflict, process conflict. This scale has gained popularity among scholars in recent years (e.g., Brykman & O'Neill, 2021; Todorova, 2020).

The discussion about the effect of the different types of intrateam conflict on team effectiveness remains active in the literature (e.g., Harvey, 2010; Humphrey et al., 2017; Maltarich et al., 2018; Mathieu et al., 2019; Susskind & Odom-Reed, 2019; Todorova, 2020). Affective and process conflict are frequently perceived as harmful to performance and attitudinal outcomes because these disagreements may cause adverse psychological reactions and operational inefficiencies, respectively (Brykman & O'Neill, 2021; Jehn, 1997; Mathieu et al., 2019). Meanwhile, the effect of cognitive conflict on team functioning and effectiveness is more complex, and it varies across types of tasks, teams, and other contextual factors (Bradley et al., 2015; De Wit et al., 2012; O'Neill et al., 2013). Whereas some studies suggest a negative impact on performance (Maltarich et al., 2018; Susskind & Odom-Reed, 2019), others argue that cognitive conflict benefits teams by preventing premature decisions and enhancing discussions of divergent viewpoints (De Dreu, 2006; O'Neill et al., 2018). Next, a more detailed discussion about the roles of different conflict types in teams found in the literature is presented.

2.3.2. Intrateam conflict and team performance

Many empirical studies have consistently found that affective conflict is negatively associated with performance outcomes and satisfaction (De Dreu & Weingart, 2003). De Wit et al. (2012) conducted a meta-analysis of the intrateam conflict literature, including some moderating variables and 116 past empirical studies. The authors found a stable negative relation between affective conflict and group outcomes. This finding was consistent with a previous meta-analysis of 30 studies conducted by De Dreu and Weingart (2003). They found that affective conflict is more disruptive than cognitive conflict for team performance. A relevant conclusion from these studies is that the negative association between affective conflict and team performance increases when cognitive conflict and process conflict display a strong association in the same study. Hence, the combined results suggest that the effects of affective conflict vary in the presence of other conflict types.

Regarding cognitive conflict, past studies suggest that its association with team performance is more complex than the relation involving affective conflict. De Dreu and Weingart (2003) early study found that cognitive conflict is equally disruptive as affective conflict for performance outcomes but less disruptive for team member satisfaction. Although the authors expected a positive cognitive conflict–performance association from an information processing perspective, their hypothesis was not supported. However, they noted that the relationship between cognitive conflict and performance is less harmful when cognitive conflict and affective conflict are weakly related, which suggests that affective conflict moderates such association. Another key finding indicates that cognitive conflict is more disruptive for teams performing highly complex (i.e., decision-making) rather than less demanding tasks.

A subsequent meta-analysis by De Wit et al. (2012) also concluded that cognitive conflict is negatively associated with attitudinal outcomes. Still, its relationship with performance outcomes was neither negative nor positive. In contrast to De Dreu and Weingart (2003)' results, the authors found that the relationship between cognitive conflict and team performance does not differ across team types. A complementary analysis of the combined effects of intrateam conflict on team performance suggested a positive relationship between cognitive conflict and team performance in the presence of affective and process conflict. De Wit et al. (2012) argued that these contrasting results are due to the difference in the number of independent samples between studies.

In addressing the call to examine the effects of intrateam conflict on team effectiveness, O'Neill et al. (2013) performed a meta-analysis on 89 studies representing 6,122 teams and 28,000 team members. The authors focused on the association between team performance, team innovation, team potency, and three types of conflict: cognitive, affective, and process conflict. Task type and teamwork settings were assessed as moderator variables. The main findings revealed that affective and process conflict are negatively associated with team performance ($p = -0.14$ and $p = -0.27$, respectively). Meanwhile, the association between cognitive conflict and performance was negative but close to zero ($p = -0.06$). Task type significantly moderated the cognitive conflict–performance association, such that the relationship was positive for decision-making teams and negative for project and production teams. The moderation effect was not significant in the affective conflict–performance association.

O'Neill et al. (2013) also explored whether the study setting (organizational, student-based, or laboratory) influenced the relationship between intrateam conflict and performance. They found that the setting type only moderates the association of affective and process conflict with performance, such that conflict is more detrimental for teams with longer passages of time and team tenure. Hence, the negative effect of affective conflict and process conflict is more attenuated in organizational settings than in laboratory or student-based samples.

To better understand the complex association between cognitive conflict and team performance, some scholars have included certain contextual conditions in the equation following the argument that cognitive conflict is not as disruptive as affective or process conflict. For instance, Bradley et al. (2012) investigated whether psychological safety provides a condition that makes cognitive conflict beneficial to team performance. A total of 117 five-person project teams were part of this study. The authors found evidence that psychological safety allows cognitive conflict to enhance performance because it creates a climate of a safe share of ideas. Other conditions that can drive a positive association between cognitive conflict and team performance include low task complexity, virtual interactions, emotional regulation, conflict management, leadership, and affective conflict (Bradley et al., 2015).

A broad consensus indicates that affective conflict and process conflict display a similar negative association with team outcomes. Regarding cognitive conflict, its implications for team functioning are still inconclusive, and it is likely to depend on other factors such as teams trust, task interdependence, or affective conflict.

2.3.3. A network perspective of intrateam conflict

Besides the contextual conditions described above, other scholars suggest that understanding the effects of intrateam conflict on team dynamics requires considering different approaches to view and measure conflict. One common criticism among academics is that most existing studies utilize compositional methods to describe team-level phenomena, which lack the richness of intrateam conflict patterns and the differences across dyadic relations. The compositional approach averages or aggregates team members' perceptions about the collective (Murase et al., 2012) while assuming that members have a shared perception or consensus about the level of conflict in the team.

Scholars have recently pointed out that conflict is not a uniform construct within a team; thus, the compositional method that aggregates individual assessment of conflict to a team-level measure does not have the sensitivity to capture the variation and complexity of the construct.

More sensitive approaches to measuring intrateam conflict have been proposed, including intrateam conflict involvement (Bachrach et al., 2014; Jehn et al., 2013) and the network view of intrateam conflict (Park, Mathieu, et al., 2020).

Intrateam conflict involvement. Jehn et al. (2013) introduced the concept of intrateam conflict involvement to describe the multilevel emergence and evolution of conflict within teams from interpersonal or dyadic occurrences. Intrateam conflict involvement is "the number of team members behaviorally engaged in a conflict in their team" (Jehn et al., 2013, p. 355). Accordingly, low intrateam conflict involvement implies that only a few members are involved in conflict with others, while high conflict involvement indicates that all members are engaged in a conflict. By focusing on dyadic experiences of conflict, this perspective considers that the effects of intrateam conflict on team dynamics and performance depend on the extent to which members are involved in a conflict and the number of members involved in such disagreement (Hood et al., 2017). Thus, the team-level conflict experience emerges from interpersonal conflicts and develops as these disagreements spread (Bachrach et al., 2014; Jehn et al., 2013).

Network conflict. Park, Mathieu, et al. (2020) noted that individuals might perceive or experience different levels of conflict with other teammates, depending on their extent of interaction. The authors indicated that despite other scholars having proposed distinct methods to examine these variations in members' perceptions of conflict, most studies still used aggregations (i.e., averages or standard deviation) to represent this construct. Alternatively, they proposed a theoretical framework of network conflict conceptualized as "a configural team state determined by members' perceived patterns of dyadic conflict with other team members" (Park, Mathieu, et al., 2020, p. 13). The network view of conflict focuses on the patterns of dyadic connections based on the perceived conflict between pairs of members. Under the network configuration of intrateam conflict, a direct tie between two members exists when one perceives conflict with the other member. A symmetric association is present when both members perceive conflict with each other. The patterns of intrateam conflict among pairs of members are the underpinnings of the network density of conflict involvement (Bachrach et al., 2014), which describes the amount of conflict across the team. Although some scholars have adopted a network perspective to characterize team conflict, the propositions from the theoretical framework developed by Park, Mathieu, et al. (2020) have not been empirically tested.

The intrateam conflict involvement perspective and the network view of conflict provided significant background to the present study. Although the original conceptualization of intrateam conflict involvement proposed by Jehn et al. (2013) focuses on the emergence of team-level conflict from dyadic expressions, it could be extended to study the implications of these dyadic occurrences of conflict using the network lens described by Park, Mathieu, et al. (2020).

2.4 TRANSACTIVE MEMORY SYSTEMS

Research on team cognition has proliferated in various disciplines over the last three decades. The accumulated empirical evidence demonstrates the primary role of team cognition in predicting team performance, and in understanding why some teams are more effective than others (Mohammed et al., 2013). Although past studies have operationalized team cognition in several ways (i.e., team learning, team knowledge, situation awareness), most of them fall into two research streams, team mental models and transactive memory systems (Sanz & DeChurch, 2013). Given the relevance of transactive memory systems for teams working on interdependent and cognitively demanding tasks, such as engineering design teams, the present study used this construct to describe team cognition.

A transactive memory system is a shared system formed by individuals' beliefs about the knowledge possessed by another and the set of transactive processes among group members to cooperatively store, encode, and retrieve information (Hollingshead, 2001; Lewis, 2004; Palazzolo, 2017). The concept of a transactive memory system was first introduced by Wegner (1987) to explain how couples manage knowledge individually and in conjunction to carry on their tasks. According to the transactive memory systems theory, individuals in close relationships rely on each other to develop expertise in specific areas and facilitate quick and coordinated access to that expertise to others (Lewis, 2003). Later, the foundations of this theory were extended to other social structures beyond intimate couples, such as organizational groups and teams (Barnier et al., 2018; Peltokorpi, 2008; Wegner, 1987).

2.4.1. General concepts of transactive memory systems

Theoretically, a transactive memory system has two essential components: an organized structure of knowledge and a set of transactive processes to maintain the memory structure (Hollingshead, 2001; Palazzolo, 2017; Ren & Argote, 2011; Wegner, 1987). The first element, called transactive memory, contains the group members' memory systems and the resulting group knowledge network (Ren & Argote, 2011; Wagner, 2014). The second component, called encoding-storing-retrieving, consists of knowledge-relevant transactive processes among group members (Brandon & Hollingshead, 2004; Wagner, 2014; Wegner, 1987). These two theoretical components illustrate a collective memory system where individuals know who knows what, which allows them to rely on one another for knowledge in specific domains (Wegner, 1987). In other words, when a transactive memory system is developed, the knowledge exchanged among individuals is stored in both individual and collective memories, and it is retrieved when needed in the future (Kush, 2019).

Although the terms transactive memory and transactive memory system are sometimes used interchangeably, they have different meanings. In short, a transactive memory resides in an individual's mind, whereas a transactive memory system results from combining individual transactive memories (Peltokorpi, 2008). According to Wegner (1987), each person possesses a memory that occurs at three stages: encoding, storage, and retrieval. The three stages have both internal and external manifestations. Internally, individuals process information in their memory facilities, meaning the three stages utilize their internal memory capacities. The external expression implies that individuals use external sources to store memory tasks or information that they cannot process internally. In such cases, individuals rely on external storage where information is retrievable.

When individuals have access to other individual memories for specific bits of knowledge, they form a knowledge-holding system that is more complex than their memories (Wegner, 1987). Thus, a group transactive memory system exists between individuals as a function of their transactive memories (Lewis, 2003). In other words, the transactive memory system of a group is only traceable through the combination of the individuals' memory systems (Wegner, 1987).

A group's transactive memory system is developed when individuals understand who possesses what knowledge and use their transactive memories to exchange and combine others' knowledge to perform common tasks (Barnier et al., 2018; Lewis, 2003). The awareness of others' knowledge enables members to direct new information entering the group to the right person(s), who accepts the responsibility of encoding, storing, and making it available for retrieval. When people take responsibility and develop expertise awareness, they can retrieve required information from the appropriate person (Peltokorpi, 2008). Then, the group transactive memory system is more likely to function effectively (Peltokorpi & Hood, 2019).

Different aspects determine the formation and operation of transactive memory systems. A primary determinant is cognitive interdependence, which implies that individuals are "motivated to share and learn what others know" (Peltokorpi, 2008, p. 379). Although individuals may perceive the collective system differently, they are expected to develop certain interdependence to enhance collaborative memory storage. Cognitive interdependence develops as people interact, learn about their areas of knowledge, and become responsible for encoding, storing, and retrieving information (Peltokorpi, 2008). Wegner (1987) suggested that this process can be fostered through members' self-disclosure, shared experiences, observations, explicit expert indications, communication, and expertise assignment, among other mechanisms. Brandon and Hollingshead (2004) suggest that individuals become cognitively interdependent in the function of task complexity and coordination demands. Therefore, the task should be interdependent enough to require members to collaborate and rely on each other to retrieve knowledge and complete common tasks (Peltokorpi, 2008).

The current literature shows that a transactive memory system develops in groups when people share responsibilities, engage in conversations about different topics, and perform interdependent tasks (Hollingshead, 1998). Prior studies also indicate that interpersonal interactions, such as intragroup communication, are the most common way to form transactive memory systems (Peltokorpi, 2008; Peltokorpi & Hood, 2019).

2.4.2. Measuring the transactive memory systems

Scholars have proposed different methods for investigating transactive memory systems by characterizing their two theoretical components (Palazzolo, 2017; Pearsall, 2008). Studies exploring transactive processes frequently adopt direct observations about the behaviors to exchange information in groups (Liang et al., 1995). In past studies, observation of related behaviors and indirect means of measurement (i.e., self-report scales) have been used to make inferences about the memory structure. Nevertheless, the latter method is usually preferred for two main reasons (e.g., Ren & Argote, 2011). First, it is difficult to fully capture a knowledge structure through observation of behaviors since it involves a cognitive state that is not tangible (Wagner, 2014). The second reason involves the challenges of implementing observation-based procedures in field studies, where groups work for longer passages of time than groups in laboratory settings (Kush, 2019). A more detailed discussion of the measurement methods adopted in past studies and related limitations is presented below.

Transactional behaviors. Early studies in laboratory settings directly assessed transactional behaviors using observational indicators. In these studies, raters watched videotapes of teams performing a task, and then they evaluated a set of predefined behaviors. Liang et al. (1995) considered three behaviors: memory differentiation (the extent to which members remember distinct aspects of the task), task coordination (the degree to which the group works together smoothly on the task), and task credibility (the extent to which members trust each other while working on the task). In observing and rating group behaviors, the researchers faced some challenges. For instance, some videotapes lack high quality, and some raters were directly involved in the study, which might have introduced some bias in their evaluation (Liang et al., 1995). The researchers included a self-assessment questionnaire to measure individuals' transactive memories and a complimentary analysis to test the effect of “non-blind” ratings (from raters involved in the study) and the rating of low-quality videotapes.

Hollingshead (1998) also utilized raters to directly assess behaviors observed in videotapes of teams working on a task. The coding system involved seven categories of relevant knowledge structure, four related to differentiated transactive memory systems and three about integrated transactive memory systems (Hollingshead, 1998). In differentiated types, the author focused on delegation of responsibility by group members, assertions of unique expertise, questions about unique expertise, and transactive retrieval of information unique to one group member. In integrated types, the interaction behaviors were assertions of shared expertise, questions about shared expertise, and transactive retrieval of shared information. Although direct observation provides relevant details on transactional behaviors, it lacks replicating studies in other settings (Wagner, 2014). Similar to the procedure followed by Liang et al. (1995), direct observation of behaviors is challenging to implement in other types of workgroups that collaborate for more extended lifecycles (Wagner, 2014).

Some other scholars have employed indirect means to investigate transactive processes in groups. Yuan, Carboni, et al. (2010) used a sociometric questionnaire to measure dyadic expertise retrieval in a multinational sales team. Expertise retrieval was measured by asking members to indicate how frequently each of their teammates provided information or advice that the respondent needed to do their job. These authors argued that focusing on dyadic interactions helps capture micro-level patterns of retrieval processes, which goes beyond the collective exploration of transactive memory systems. Yuan, Fulk, et al. (2010) used a similar approach to characterize expertise exchange among members of 18 organizational teams. Team members were asked to report whether they had retrieved information from or allocated information to their teammates in specific knowledge areas. A composite score representing individuals' expertise exchange was computed based on their responses.

These studies prove that the relational view of transactive processes allows for examining how different transactive patterns contribute to collective functioning. The indirect measurement method allows researchers to collect information about transactive retrieval in teams that are geographically distributed and interact through various channels (i.e., email, telephone, conference calls). Indirect measures were more accessible and more efficient to implement than observing behaviors.

Transactive memory structure. Faraj and Sproull (2000) proposed an 11-item questionnaire to indirectly measure three dimensions of expertise coordination: knowing expertise location (how the knowledge is distributed across the team), recognizing the need for expertise (when and where expertise is needed), and bringing expertise to bear (ways by which expertise is brought to take on a problem). This scale was validated in a sample of student project teams. The authors concluded that the scale shows evidence of reliability and construct validity. However, this is the only study that has examined the adequacy of the scale in different settings.

Austin (2003) proposed a different measurement method to assess the cognitive structure of transactive memory systems. This measure focuses on four dimensions: group knowledge stock, consensus about knowledge resources, specialization of expertise, and accuracy of knowledge identification. The author interviewed participants to identify knowledge domains relevant to the task. Then, a self-assessment questionnaire was employed to measure the first dimension, while a peer-rating scale was used to assess the specialization of expertise and consensus about knowledge resources. Similar to other measurements above, this approach needs more replicating research.

The scale developed by Lewis (2003) is perhaps the predominant tool to indirectly assess the structure of transactive memory systems. The author integrated into a 15-item self-assessment questionnaire the three behavioral indicators proposed by Liang et al. (1995). Hence, the scale is said to measure three behavioral indicators of the transactive memory structure: knowledge specialization (the tendency for members to recall various aspects of the task), task credibility (how much members confidently rely on others to accomplish common tasks), and task coordination (how effective team members integrate their transactive knowledge) (Kush, 2019; Wagner, 2014). The author validated this scale in three studies, including one laboratory and two field studies. Other subsequent studies have supported the psychometric qualities of this scale (Kush, 2019; Todorova, 2020).

Measurement scales provide some advantages over other methods. Measurement scales can be consistently and efficiently applied to different workgroups, even in distributed groups. Using indirect measures is less costly and time-consuming since the collected data does not need to be coded to represent the constructs. However, indirect measures come with limitations. For instance, measurement scales only measure perceptions about how a transactive memory system is used, so it is impossible to capture how the actual knowledge is structured (Mesmer-Magnus et al., 2017). Hence, measurement scales only allow researchers to infer the use of transactive memory structures from manifest variables (Lewis, 2003; Lewis & Herndon, 2011).

Although the multiple approaches used to assess transactive memory systems provide reliable representations of the two theoretical components (Kush, 2019), they adopt different assumptions. Studies examining transactive memory systems through cognitive manifestations assume the existence of transactional communication of expertise among group members. Studies viewing transactive memory systems through transactional behaviors implicitly assume a cognitive structure and shared awareness of knowledge in the group (Pearsall, 2008). Some scholars have proposed a combination of measurement methods to capture the cognitive manifestation of the memory structure and the transactive processes to capture the construct extensively (Wagner, 2014).

In sum, past research highlights some essential indicators for characterizing transactive memory systems' structural and transactive components in teams. Nevertheless, most studies often focus on only one theoretical component (Kush, 2019). Thus, a prevalent call for research involves investigating both elements of transactive memory systems (Barnier et al., 2018; Kush, 2019; Wagner, 2014).

2.4.3. Transactive memory systems and performance in teams

The positive relationship between team transactive memory systems and performance has been supported in several studies in various groups and tasks. It has been found that teams with well-developed transactive memory systems generate higher quality products and products that satisfy clients' needs and are more likely to complete their projects on time (Hollingshead, 1998; Lewis, 2003). A transactive memory system also enhances collective learning, trust, satisfaction, and team creativity (Hollingshead, 2001; Zhou & Pazos, 2020).

The relationship between transactive memory systems and different team outcomes has been examined in three meta-analyses. Turner et al. (2014) reviewed six forms of team-shared cognition and their relationship with team performance. The authors studied four independent samples regarding transactive memory systems, involving 964 participants and 316 units. Results indicated that transactive memory systems displayed a significant association with performance.

However, this association was weaker than those involving shared mental models and cognitive congruence.

Mesmer-Magnus et al. (2017) updated a preliminary study conducted by DeChurch and Mesmer-Magnus (2010) about team cognition and its role in team processes and performance. They focused specifically on shared mental models and transactive memory systems. Results supported previous evidence about the positive effects of team cognition on team behavioral processes (e.g., goal specification, monitoring progress) and performance (e.g., ratings of work quality). Nevertheless, the authors did not examine both forms of team cognition separately.

A more extensive meta-analysis than the studies described above is found in Bachrach et al. (2019), who examined the transactive memory system-performance relationship. This meta-analysis included 76 empirical studies involving 6,869 teams. In investigating team performance, three aspects were considered: task-based (i.e., quality of solution, task completion time), affective (i.e., cohesion, satisfaction), and creative performance (creativity, innovation). Results indicated that the transactive memory system is positively and significantly related to the three types of performance.

Bachrach et al. (2019) also investigated contextual factors that function as antecedents of the development of transactive memory systems: environmental context, leadership context, team human capital, and team diversity. Results from this analysis showed that environmental volatility, which captures the dynamism of the market, and leadership effectiveness, referred to as the extent to which leadership behaviors are present, are positive and significantly related to transactive memory systems. Two aspects of team diversity, functional background and gender diversity were negatively related to transactive memory systems.

Other empirical studies have explored diverse potential drivers of transactive memory systems. Existing evidence suggests that task incentives (Hollingshead, 2001), role identification behaviors (Pearsall et al., 2010), team-skills training (Prichard & Ashleigh, 2007), team member familiarity (Lewis, 2004), task interdependence, cooperative goal interdependence, support for innovation (Zhang et al., 2007), communication volume and frequency (Jackson & Moreland, 2009; Lewis, 2004; Peltokorpi & Manka, 2008), and social interaction quantity (Millsaps, 2020) are critical drivers of transactive memory systems.

Past research has demonstrated the positive impact of transactive memory systems on teams' performance. Scholars have also provided evidence of distinct mechanisms that enhance the development of these systems. However, most previous studies focus on enablers, while fewer studies have examined the factors that may disrupt the development and functioning of transactive memory systems in teams.

2.5 THE NETWORK PERSPECTIVE OF TEAMS

Social network theory provides an alternative framework to understand the structure of team members' interactions, team processes, team states and to model the impact of patterns of relationships in teams at multiple levels and over time (Contractor, 2011). Past studies support that network analysis methods are sensitive in capturing modern teams' complexity and dynamism (Murase et al., 2012). This alternative approach captures the different configurations of team-level constructs and may overcome the limitations derived from the assumption of uniform shared perception frequently adopted in prior research (Park, Mathieu, et al., 2020). Accounting for individual differences and dyadic configurations through which team-level constructs emerge becomes a valuable tool for investigating how teams and their members accomplish their goals (Humphrey & Aime, 2014; Park, Grosser, et al., 2020).

Given that group members' interactions are inherent to completing common tasks and developing team cognition, characterizing transactive processes as networks align with the information processing theory and offers insights into how these processes develop and function (Lewis & Herndon, 2011). Similarly, a social network perspective provides a more sensitive articulation of intrateam conflict configurations than the traditional approach based on the aggregation of individuals' perceptions about the collective (Park, Mathieu, et al., 2020), thus becoming a valuable tool for advancing research in this field (Humphrey et al., 2017; O'Neill & Mclarnon, 2018).

Although the network structures can be described at multiple levels, dyadic configurations and network density are presumed to capture teams' micro and macro levels. As Humphrey and Aime (2014) and Humphrey et al. (2017) noted, dyads are the core components of teamwork because it is through these interpersonal interactions that team members organize and carry on their team activities. Adopting the description by Yang et al. (2019), a dyad in a group represents a pair of members who are tied through behavioral, affective, or cognitive relations. These patterns of relations occurring within dyads are the building blocks of network density, which describes the collective group structure (Brass & Borgatti, 2020). Density shows how connected the whole group is as the ratio of existing relations divided by the total possible relations among group members (King & Sweet, 2020; Wasserman & Faust, 1994).

Accordingly, dyadic relationships were adopted to characterize intrateam conflict, communication, and expertise retrieval patterns. Network density represents the same variables at the group level. Network measures for weighted relations were used in this study. The reason for using these measures is that the reported intrateam conflict, communication, and expertise retrieval networks used valued data, meaning that they account for the values assigned for each respondent in the corresponding scale.

In summary, a social network perspective might provide a complete understanding of the transactive memory system at different levels, the communication patterns that influence the formation and function of these systems, and the different patterns of intrateam conflict among members that might affect this association. The research adopted a network-based approach to characterize dyadic and group-level constructs that needed to be fully applied in previous studies on team cognition.

2.6 THE RESEARCH MODEL

A transactive memory system is a shared system formed by individuals' beliefs about the knowledge possessed by another and the set of transactive retrieval processes among group members to access relevant knowledge (Hollingshead, 2001; Lewis, 2004). The accumulated literature indicates the benefits of transactive memory systems translate into higher quality products, products that better meet clients' needs, and timely completion of team projects (Hollingshead, 1998; Lewis, 2003). Given the relevance of team cognition, the present study examined the roles of cognitive and affective conflict emergence in the relationship between intrateam communication and transactive memory systems. This study accounted for the structural transactive components in testing the proposed relationships.

This study relied on the three behavioral indicators proposed by Lewis (2003) to assess the structural component of transactive memory systems. Accordingly, teams with functional transactive memory systems are presumed to be composed of members who collectively rely on each other to accomplish common tasks, coordinate processes, and effectively integrate task-relevant knowledge. Concerning the transactive component, the frequency of expertise retrieval between team members adopting the Yuan, Carboni, et al. (2010)'s approach was studied.

The remaining content of this section discusses the interaction between communication, intrateam conflict, and transactive memory systems. It concludes with the hypotheses' development and the statistical model.

Intrateam communication. Communication has been highlighted as a core factor in the emergence and operation of transactive memory systems in teams (Peltokorpi, 2008; Peltokorpi & Manka, 2008). Hollingshead and Brandon (2010) concluded that communication allows members to recognize each other's skills and knowledge, facilitating expertise recognition, allocating roles, and improving accuracy in expertise retrieval (Hollingshead, 1998). Communication benefits have been hypothesized to hold over time, with members' initial interactions allowing the emergence of transactive memory systems and communication frequency playing a pivotal role in their development and maturity (Hollingshead, 1998; Lewis, 2004).

Most studies have found general support for the positive relationship between communication and transactive memory systems (Argote et al., 2018; Palazzolo et al., 2006; Peltokorpi & Hood, 2019; Yuan, Fulk, et al., 2010). However, there is still a debate among some scholars regarding the conditions that allow communication to support the development of team cognition (Su, 2021). For instance, Yan et al. (2021) found that the role of communication depends on the dimensions or attributes considered in its operationalization. While this study built on the overall evidence that communication is an essential predictor of transactive memory systems, it focused on three critical aspects of communication quality. Communication was not only viewed as a process to transfer information, but it was assessed in terms of its frequency, openness, and directness, which are key for developing team cognition.

A subset of empirical studies has examined the relationship between communication and transactive memory systems using a network lens. For instance, Pulles et al. (2017) noted that network ties reflecting interpersonal interactions positively predicted credibility and task coordination in university research and development groups. Argote et al. (2018) found that communication density in stable groups (groups without turnover) contributed to developing more robust transactive memory systems and better performance than groups that experienced turnovers.

Recently, two extensive reviews supported that communication networks set favorable conditions for developing transactive memory systems. Peltokorpi and Hood (2019) concluded that the strength of communication network ties was related to group members' expertise awareness. Furthermore, team members' accuracy in expert recognition was positively influenced by one's degree of centrality in the communication network. Yan et al. (2021) noted that communication patterns through various channels such as face-to-face and computer-mediated are beneficial for transactive memory systems and that groups may benefit from formal and informal communication. According to the literature, a positive association between intrateam communication networks and transactive memory systems was expected.

In adopting a network perspective, intrateam communication was characterized as a network connecting team members regarding the perceived quality of their interaction. Dyadic communication quality was estimated based on the reported communication quality that each member perceived with others. At the group level, communication quality density represented the group-level quality of communication resulting from the perceived communication patterns within dyads. This approach was expected to capture the intricacies of communication quality as it did not assume that communication was homogeneous across the team.

Besides the direct relationship between communication quality and transactive memory systems, it was proposed that this association was influenced by intrateam conflict at the dyadic and group levels. We know from the literature that communication networks allow members to access and exchange information, thus facilitating the development of transactive memory systems. However, team members' involvement in conflict can alter how the information is communicated, processed, and consolidated into a transactive memory system, either by disrupting members' attention capacity or increasing information processing depth. The hypothesized roles of task and relationship conflict on transactive memory systems were grounded on the information-processing perspective, which suggests that the emergence of intrateam conflict can disrupt communication and information flow across the team (Gibson, 2001; Staw et al., 1981).

Intrateam conflict. Intrateam conflict is inherent in interdependent work (O'Neill & Mclarnon, 2018) that requires group members to conciliate values, viewpoints, and preferences to function collectively and achieve common goals (Jehn, 1995; Lovelace et al., 2001). The literature on team conflict distinguishes two main types of intrateam conflict that emerge within teams: cognitive and affective (Behfar et al., 2011; De Wit et al., 2012; Mathieu et al., 2019). Despite the emergency nature of intrateam conflict in teams, there is still little research focusing on its relationship with communication and transactive memory systems.

The intrateam conflict that emerges in groups can alter how the information communicated among members is processed and consolidated into a transactive memory. Perceived divergent ideas and opinions about the task and how it is performed may uncover new information and insights, enhancing discussions and the depth of information processing necessary to perform interdependent tasks (Hinsz et al., 1997; Park, Mathieu, et al., 2020). Conversely, affective conflict is likely to negatively affect task-related discussions and communication patterns because it emerges from interpersonal or emotional disputes that can divert individuals' attention to matters irrelevant to the collective tasks (Bodenhausen, 1993; Peltokorpi & Hood, 2019).

Some scholars have investigated the relationship between intrateam conflict and transactive memory systems (Hood et al., 2014; Peltokorpi & Hood, 2019), but their work mainly focuses on how conflict moderates or mediates the transactive memory systems - performance outcomes association (e.g., Rau, 2005; Riley & Ellegood, 2019). Conversely, it was proposed that cognitive and affective conflict interact and moderate the influence of intrateam communication on transactive memory systems. This view was in line with Gibson (2001) and Staw et al. (1981), who noted that different types of intrateam conflict affect information processing by shaping the information flow across the team. Given the critical role of communication in developing team cognition, the disruption that intrateam conflict creates on the patterns of information exchange was expected to influence transactive memory systems.

Other related literature has discussed the implications of intrateam conflict on information processing from the perspective of limited capacity and resource losses (Bachrach et al., 2014; De Wit et al., 2012; De Wit et al., 2013; Peltokorpi & Hood, 2019; Todorova, 2020). For instance, Bachrach et al. (2014) argued that the more conflict exists, the fewer resources are available to complete the team's tasks. In focusing on affective conflict, Pelled (1996) exposed that such conflict detriments the members' capacity to assess incoming information and makes them less receptive to others' ideas. Nevertheless, most studies within this literature relied on compositional measures, which assume homogeneity in individuals' experiences of intrateam conflict.

Recently, it has been noted that individuals may perceive or experience different degrees of conflict with their teammates as they may interact differently with each other (Hood et al., 2017; Maltarich et al., 2018; Park, Mathieu, et al., 2020). The concept of intrateam conflict involvement proposed by Jehn et al. (2013) was presumed to capture the intricacies of intrateam conflict resulting from different patterns of perceived disagreements (Humphrey et al., 2017; O'Neill & Mclarnon, 2018). Similarly, Park, Mathieu, et al. (2020) argue that conflict is not likely to be experienced homogenously across the team because individuals may be involved in more conflict with some members than with others. In response, they proposed a theoretical framework of conflict networks, which considers a conflict network as the individuals' perceived patterns of disagreements with other group members (Park, Mathieu, et al., 2020).

There has been some interest in incorporating a relational conceptualization of conflict to understand its multilevel structural characteristics and implications for individual and team outcomes. For instance, Jen (2013) studied the relationship between individuals' degree centrality within two conflict networks and job performance and satisfaction. For this purpose, the degree of centrality of an individual within these conflict networks indicated their amount of conflict relations with others. While degree centrality in the affective conflict network is negatively associated with individual outcomes, a positive relationship was found between degree centrality in the cognitive conflict network and individual performance and satisfaction.

Humphrey et al. (2017) focused on the dyadic configuration of conflicts to investigate how cognitive and affective conflict among pairs of members affect information exchange and team performance. Some key findings from this study suggest that information exchange decreases when high levels of affective conflict in any dyad are present in a team. Conversely, cognitive conflict exhibits a positive association with information exchange and performance. Another related study conducted by Bachrach et al. (2014) investigated the mediating mechanism of the cognitive, affective, and process conflict network density between transactive memory systems and team performance. Network density was used to represent the extent to which conflict relations are perceived among team members. It was found that only cognitive and affective conflict density have significant mediating effects.

The literature presented above provided empirical evidence that intrateam conflict can be examined at multiple levels through a network perspective. The proposed study focused on the dyadic and group-level configurations. The dyadic intrateam conflict represented the extent to which every pair of members was involved in a conflict. The density of the conflict network described the overall team conflict as an aggregate of all the dyadic conflict patterns. A conflict network was expected to portray the intricacies of interpersonal conflicts across the team because it focused on how individuals perceived conflict with one another.

Intrateam conflict was expected to influence the association between communication and transactive memory systems at the dyadic and group levels. More specifically, cognitive conflict was introduced as a factor that directly interacted with communication, while affective conflict was expected to moderate the effect of cognitive conflict. The interaction between cognitive and affective conflict was based on the argument from the information processing theory suggesting that intrateam conflict types are not independent of each other such that cognitive conflict needs to be studied in the context of non-task-related disagreements (O'Neill et al., 2018). Similarly, previous empirical work in different contexts suggests that the benefits of cognitive conflict are mostly perceived under low levels of affective conflict (Bradley et al., 2015; De Wit et al., 2012;

Pazos et al., 2022). The proposed moderation model described below accounted for the interdependency between cognitive and affective conflict.

Although increasing attention has been paid to team cognition drivers, more research is needed investigating the roles of cognitive and affective conflict on transactive memory systems (Peltokorpi & Hood, 2019; Todorova, 2020; Yan et al., 2021). Next, the research hypotheses are presented.

2.6.1 Hypotheses development

The growing empirical evidence suggests that intrateam communication enables retrieval processes and the transactive memory structure. Hollingshead (1998) and Hollingshead and Brandon (2010) argue that communication allows members to recognize each other's skills and knowledge, fostering the development of transactive memory systems. At the dyadic level, past research has shown that the extent to which a pair of members communicate positively predicts their interactions to seek information during taskwork (Yuan, Carboni, et al., 2010). Team members who interact frequently can develop a communication channel pathway, which is more likely to be used for knowledge sharing because it requires less time and effort than starting interactions with whom communication is scarce (Su, 2021). Other related studies have shown that frequent interactions allow members to build trust in one another (Yan et al., 2021) and develop implicit and explicit coordination (Reimer et al., 2017). Research on communication networks has supported the positive relationship between interpersonal ties' strength and task credibility, task coordination, and expertise exchange (Pulles et al., 2017; Yuan, Fulk, et al., 2010). Furthermore, it has been found that communication network density contributes to developing robust transactive memory systems because it allows teams to deal with emergent situations such as turnover (Argote et al., 2018).

The literature suggests that communication sets favorable conditions for developing transactive memory systems. In placing communication as the central predictor of transactive memory systems, it is proposed that frequency, openness, and directness are crucial attributes that capture the quality of communication between individuals.

Hypothesis 1a (H_{1a}): Dyadic communication quality will be positively associated with dyadic expertise retrieval.

Hypothesis 1b (H_{1b}): Communication quality density will be positively associated with the transactive memory system use.

Cognitive conflict as moderator

Cognitive conflict is about perceived differences due to divergent ideas and viewpoints about the task's content and outcomes (Humphrey et al., 2017; Jehn, 1995). Cognitive conflict is likely to strengthen the benefits of intrateam communication for transactive memory systems because it reflects individuals' willingness to share their viewpoints, despite having divergent perspectives (Moye & Langfred, 2004). Because this type of conflict is task-related rather than interpersonal, it does not limit access to informational resources or deviates individuals' attention compared to non-task-related conflicts (Hu et al., 2019). Indeed, early work by Amason (1996) and Simons and Peterson (2000) suggests that cognitive conflict enhances the quality of discussions among members by bringing alternative perspectives and diverse ideas.

Similarly, Lee (2014) and Meng et al. (2015) argued that cognitive conflict motivates individuals to exchange information to resolve inconsistencies regarding divergent viewpoints about the task and understand each other's opinions and preferences. By disclosing their divergent perspectives, group members have more chances to learn about others than when these discussions are scarce. Cognitive conflict will likely enhance the relationship between communication and transactive memory systems as team members become less reluctant to share their views and thoughts within the group. The positive moderation effect of cognitive conflict is expected to hold at the dyadic and group levels. Regarding dyads, the cognitive conflict between group members is expected to moderate the relationship between communication and expertise retrieval. Cognitive conflict density will display a positive moderation at the group level. Hence, it is proposed that:

Hypothesis 2a (H_{2a}): Dyadic cognitive conflict positively moderates the relationship between dyadic communication quality and dyadic expertise retrieval.

Hypothesis 2b (H_{2b}): Cognitive conflict density positively moderates the relationship between communication quality density and the transactive memory system use.

The interaction between cognitive and affective conflict

Affective conflict involves perceptions of interpersonal incompatibilities and emotional tensions among group members (Jehn, 1995). Conversely to cognitive conflict, affective conflict impairs members' interactions and ability to process task-relevant information because of perceived hostile relations. The negative emotions created by affective conflict can make group members less likely to gain comfort from others (Hu et al., 2019) and less receptive to others' ideas regarding the tasks (Pelled, 1996). In reaction to perceived affective conflict, members can withdraw from team activities and withhold information to avoid re-escalation of conflict (Labianca & Brass, 2006; Sparrowe et al., 2001).

In line with the argument that cognitive conflict must be examined in the context of other disagreements (O'Neill et al., 2018), affective conflict was expected to negatively interact with cognitive conflict and moderate its effects on the association between communication and transactive memory systems. Pelled (1996) argued that affective conflict could reduce the benefits of cognitive conflict by limiting group members' ability to assess others' opinions critically and by consuming their time and energy, which otherwise could be used to resolve more substantive disagreements. Previous work on the interaction between affective and cognitive conflict from an information processing perspective suggests that high interpersonal incompatibilities overuse teams' cognitive resources and limit their capacity to complete team tasks (Bradley et al., 2015). The co-occurrence of cognitive and affective conflict has been examined using a network lens. For instance, Marineau et al. (2018) found a positive association between cognitive conflict and information seeking in dyads when affective conflict relations were absent. The following hypotheses are proposed:

Hypothesis 3a (H_{3a}): The interaction between dyadic affective conflict and dyadic cognitive conflict will negatively moderate the positive relationship between communication quality and expertise retrieval, such that the higher the affective conflict, the weaker the moderation effect of cognitive conflict.

Hypothesis 3b (H_{3b}): The interaction between affective conflict density and cognitive conflict density will negatively moderate the positive relationship between communication quality density and the transactive memory system use, such that the higher the affective conflict density, the weaker the moderation effect of cognitive conflict density.

In summary, intrateam conflict is hypothesized to moderate the intrateam communication-transactive memory systems association. While cognitive conflict was expected to display a positive moderation effect, affective conflict was considered detrimental by negatively interacting with cognitive conflict. Figure 1 depicts the proposed research model. Table 2 summarizes the research hypotheses and their link to the research questions.

Figure 2.

Proposed research hypotheses.

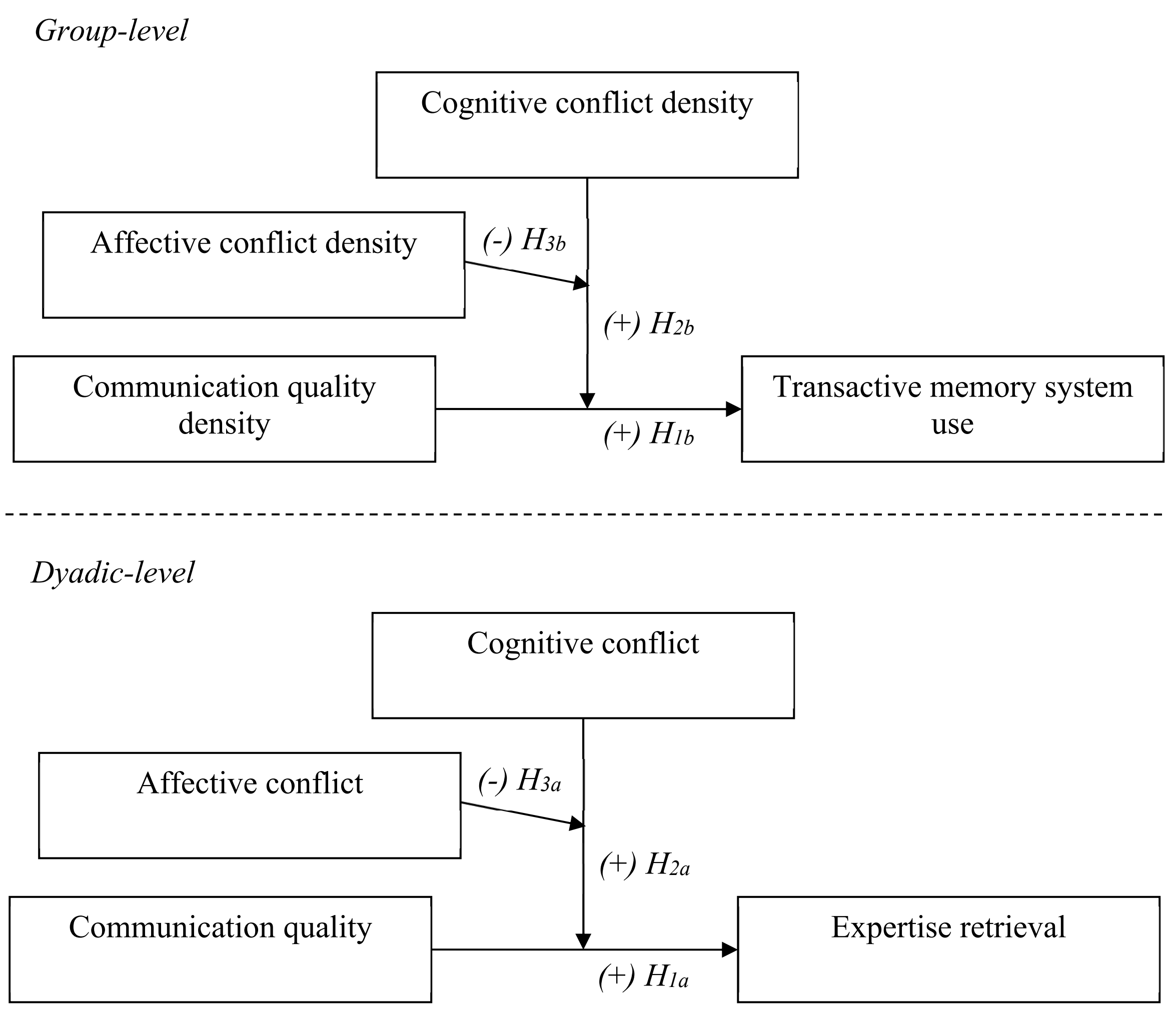


Table 2.

Summary of research questions and hypotheses

RQ.	Sub-questions	Hypothesis	Variables	Indicators	Analysis
1	How does intrateam communication relate to transactive memory systems at the dyadic level?	H_{1a}	Communication quality Expertise retrieval	Dyadic communication quality Dyadic expertise retrieval	Hierarchical linear model
	How does intrateam communication relate to transactive memory systems at the group level?	H_{1b}	Communication quality density Transactive memory system use	Communication network density Composite of transactive memory system behavioral indicators	Hierarchical regression
2	Does cognitive conflict moderate the relationship between intrateam communication and transactive memory systems at the dyadic level? If so, how?	H_{2a}	Communication quality Cognitive conflict Expertise retrieval	Dyadic communication quality Dyadic cognitive conflict Dyadic expertise retrieval	Hierarchical linear model
	Does cognitive conflict moderate the relationship between intrateam communication and transactive memory systems at the group level? If so, how?	H_{2b}	Communication quality density Cognitive conflict density Transactive memory system use	Communication network density Cognitive conflict network density Composite of transactive memory system behavioral indicators	Hierarchical regression

Table 2.

(*continued*)

RQ.	Sub-questions	Hypothesis	Variables	Indicators	Analysis
3	Does affective conflict interact with cognitive conflict in shaping the relationship between intrateam communication and transactive memory systems at the dyadic level? If so, how?	H_{3a}	Communication strength	Dyadic communication quality	Hierarchical linear model
			Cognitive conflict	Dyadic cognitive conflict	
			Affective conflict	Dyadic affective conflict	
			Expertise retrieval	Dyadic expertise retrieval	
	Does affective conflict interact with cognitive conflict in shaping the relationship between intrateam communication and transactive memory systems at the group level? If so, how?	H_{3b}	Communication quality density	Communication network density	Hierarchical regression
			Cognitive conflict density	Cognitive conflict network density	
			Affective conflict density	Affective conflict network density	
			Transactive memory system use	Composite of transactive memory system behavioral indicators	

2.7 SUMMARY

The literature generally supports the positive relationship between intrateam communication and team performance (Kozlowski & Bell, 2003; Kozlowski & Ilgen, 2006). It is also known that communication networks facilitate the development of transactive memory systems by allowing team members to access and exchange information (Peltokorpi & Hood, 2019). However, questions remain regarding the factors that may disrupt the association between communication and the development of transactive memory systems in teams (Su, 2021; Yan et al., 2021).

The team literature grounded on the information processing theory suggests that emergent conflict plays a critical role in forming team cognition. Gibson (2001) and Staw et al. (1981) noted that different types of intrateam conflict affect information processing by shaping the information flow across the team. Team members' involvement in conflict can alter how the information is communicated, processed, and consolidated into a transactive memory system, either by disrupting members' attention capacity (affective conflict) or increasing information processing depth (cognitive conflict) (Bradley et al., 2015; Hu et al., 2019; Peltokorpi & Hood, 2019).

The hypothesized roles of cognitive and affective conflict on transactive memory systems were grounded on the information-processing perspective and the literature on emergent conflict and team effectiveness. Given the critical role of communication in developing team cognition, understanding the role of intrateam conflict in moderating the patterns of information exchange is relevant to advance theory and research on team cognition.

CHAPTER 3

METHODOLOGY

3.1 INTRODUCTION

This study investigated how cognitive and affective conflicts influence intrateam communication and shape a team's transactive memory systems and expertise retrieval in project teams. A theoretical model displaying the hypothesized relationships between these variables was built from the information processing theory and existing literature. The proposed relationships were deductively tested using data collected using previously developed scales. The present chapter describes the methodology adopted to test the research hypotheses. The content of this chapter includes the research design, the selection of participants, the variables and measurement instruments, and the data collection and analysis procedures.

3.2 STUDY DESIGN

This study adopted a quantitative approach and design grounded on the post-positivism paradigm (Creswell & Creswell, 2017). Research under this worldview focuses on problems involving relationships among variables (deterministic). These relationships are formalized and reduced in terms of hypotheses and research questions (reductionism). The knowledge developed under this paradigm is shaped by empirical measurement of the objective reality (empiricism). Data collected from measurement scales are used to develop relevant conclusions concerning the relationships between the variables of interest (verification). Furthermore, given that the absolute truth of knowledge cannot be asserted when human behaviors and actions are studied (Creswell & Creswell, 2017), data and evidence were used to identify specific claims that are more likely than others. These major elements informed the present study.

A non-experimental time-lag design that relies on quantitative data collection and analysis methods was adopted. A survey method was used to collect numeric measurements of the variables under study. The data collected were analyzed using statistical procedures. Statistical analysis tools are widely accepted to test associations among variables and answer the research questions in quantitative research (Creswell & Creswell, 2017). Specifics about the research methods are discussed next.

3.3 STUDY SAMPLE

3.3.1 Participants

The sample of this study consisted of engineering students working in temporary project teams. Undergraduate engineering students working on engineering design projects and graduate engineering students working on systems analysis and design projects as part of their coursework were recruited through convenience sampling. Instructors of capstone courses in the College of Engineering and Technology were asked to provide support with the data collection process by (1) providing access to the first sessions to inform potential subjects about the research project and invite them to participate, (2) providing a description of the teams' projects at the beginning of the collaborative work, and (3) facilitating survey distribution. With the support of three instructors, individuals enrolled in mechanical and aerospace engineering, engineering technology, and engineering management and systems analysis disciplines were invited to be part of the study between the Summer of 2022 and the Spring of 2023.

The research study, including participant recruitment and data collection, was approved as exempt by the human subject research Institutional Review Board.

3.3.2 Characteristics of the team projects

The sample included teams performing two types of projects: engineering design and systems analysis and design. The engineering design teams included undergraduate students working on design ideas and product realization to address real-world engineering problems. They worked on various designs to apply mechanical engineering concepts and new technology trends, including autonomous and intelligent vehicles and advanced structures and systems using innovative designs. These projects were completed over two semesters. The first period focused on project planning, and the second period consisted of the execution of the design idea and prototyping. This study focused on the second period of the project.

The systems analysis and design teams included graduate engineering students who worked on analyzing organizational systems as part of a semester project. They proposed innovative designs to optimize such systems considering social, structural, operational, and environmental aspects. The teams used systems theory and analysis to identify problems, diagnose root causes, and develop solutions. The project was completed over one semester and divided into planning and execution stages.

The participating teams were exposed to similar project requirements and demands. First, the engineering design and systems analysis teams were purposefully designed by the instructors to incorporate elements such as interdisciplinary work, tools to facilitate virtual collaboration and communication, constituents that acted as clients or stakeholders, time constraints, and design projects that addressed real-world problems. Second, project characteristics such as complexity or weighted group rewards over individual rewards (i.e., weighted grading based on peer feedback) that have been shown to induce team members to work interdependently (Martin et al., 2011; Zhou & Pazos, 2014) were common across teams.

Differences in student level were acknowledged and mitigated through two strategies. First, a statistical test examined whether the response variable varied based on project type. Second, a control variable reflecting teamwork experience was included to account for potential differences in incoming group collaboration expertise. There was no evidence to indicate that the differences in project type or levels of experience affected the results.

About using student-based teams

Certain limitations regarding the generalizability of results from student-based samples to professional settings are part of an ongoing discussion in the literature. For instance, differences in motivational factors driving performance are common between student and organizational teams (Todorova, 2020). Nevertheless, past studies have demonstrated that using study settings that approximate professional contexts can mitigate these limitations (Hood et al., 2017; Lewis, 2004; Todorova, 2020). Building on these antecedents, the sample of teams was selected considering certain project characteristics and demands that are common in engineering teams working in professional environments (i.e., interdependency, time constraints, virtual work) (Borrego et al., 2013; Jenkins & Lackey, 2005). Such characteristics were expected to strengthen the external validity.

3.3.3 Sample size

A preliminary estimate of the required sample size was based on a power analysis performed in *WebPower* (Zhang & Yuan, 2018) using the following coefficients for a two-level hierarchical linear model: *power* = 0.8, effect size (f^2) =0.25, *alpha* = 0.05*, ICC* = 0.10. The parameters were specified considering a within-cluster two-level model with no cross-level interactions estimated using Restricted Maximum-Likelihood estimation (REML). The values of the coefficients follow the recommendations discussed in Arend and Schäfer (2019) for detecting a minimum acceptable statistical power with medium effect size, small between-groups variance, and conventional significance level, which are common in behavioral research. The results of the analysis suggested a sample size of 210 level-one observations. Since the level-one variables were based on dyads, the recommended sample size of 210 dyadic observations could be obtained from 35 teams, assuming an average of four members.

Following the sample size recommendation, an initial sample included 238 individuals representing 50 teams. Nevertheless, the final sample was reduced to 189 individuals from 44 teams due to incomplete responses or negative answers in the consent forms. The final sample provided 874 directed dyads, which were considered appropriate to test the hypothesized model based on the preceding power analysis.

3.4 VARIABLES AND INSTRUMENTS

3.4.1. Communication quality and density

Intrateam communication refers to the process through which individuals interact to exchange information within the team (González-Romá & Hernández, 2014; Johnson & Lederer, 2005). Communication was defined in terms of the perceived quality of interactions to exchange information between individuals within a team. This variable was measured using a three-item scale from Peltokorpi and Manka (2008). The scale measured the perceived quality of communication between team members, which is assumed to represent the quality of the actual process accurately. The scale was presented on a seven-point scale, from 1=strongly disagree to 7=strongly agree. The scale items were displayed in a peer-rating format where each member assessed their communication quality with every other member. This approach provides an indicator of communication that facilitates the assessment of communication between all members of a team and an aggregate measure for the overall team. The preliminary internal consistency of the scale is Cronbach's alpha = 0.70 (Peltokorpi & Manka, 2008). An example item is "I communicate frequently with [X]." Responses were converted into an adjacency matrix for each team to estimate dyadic communication quality and communication density.

3.4.2. Cognitive and affective conflict

Intrateam conflict is defined as the members' perceptions about the intensity of either tasks or interpersonal disagreements (DeChurch et al., 2013). Cognitive and affective conflict were measured using the scale developed by Behfar et al. (2011). The instrument showed acceptable internal consistency ($\alpha > 0.80$ for each subscale) and acceptable model fit from the confirmatory factor analysis (factor loadings < 0.3 for each factor) in the scale development study (Behfar et al., 2011). The original scale includes four items on a seven-point scale (1=none/not at all, 7=always/totally) for each conflict type. The number of items was reduced to three for each conflict to minimize survey length and respondents' fatigue. The adapted version of the scale was presented in a peer-rating format so that participants assessed their conflict involvement with each of their teammates. An example item of cognitive conflict is "How often do [X] and you engage in debate about different opinions or ideas?". An example item of affective conflict is "How much are personality conflicts evident between you and [X]?". Responses were converted into an adjacency matrix for each team. This arrangement displayed the patterns of dyadic intrateam conflict and the intrateam conflict density.

3.4.3. Transactive memory systems use.

A transactive memory system is a shared system formed by individuals' beliefs about the knowledge possessed by another and the set of transactive processes among group members to cooperatively store, encode, and retrieve information (Hollingshead, 2001; Lewis, 2004; Palazzolo, 2017). The Behavioral Indicators of Transactive Memory Systems' scale developed by Lewis (2003) was used to make inferences about the extent to which the transactive memory system was used. Accordingly, perceptions about the levels of expertise awareness, task credibility, and task coordination within a team were used to prove the transactive memory system's operation. The original scale contains 15 items (five items per indicator) on a 5-point scale (1=strongly disagree, 5=strongly agree). This study used a shortened version with nine items (three items per indicator) to reduce the survey length. Previous research suggests that shorter peer-rating scales are psychometrically reasonable to make the survey less exhausting to the participants (Humphrey & Aime, 2014). A similar nine-item scale used by Marques-Quinteiro et al. (2013) showed acceptable internal consistency (Cronbach's alpha = 0.75). An example item of task coordination is "Our team had very few misunderstandings about what to do." Participants' responses were aggregated to represent a group-level variable called transactive memory system use.

3.4.4. Expertise retrieval

Expertise retrieval was defined as the perceived frequency to which information and knowledge are retrieved between two team members. The measurement of expertise retrieval followed a similar approach used in Yuan, Carboni, et al. (2010) and Yuan, Fulk, et al. (2010), which asked members to indicate how frequently each of their teammates provided information or advice that the respondent needed to do their job. A third item from Borgatti and Cross (2003) asking participants how often they turned to each of their teammates to retrieve information and knowledge was also included. These items were displayed in a peer-rating format using a seven-point scale (1=very infrequently, 7=very frequently). A sample item is “How frequently has [X] provided information or knowledge that you would need to do your job?”. Responses were converted into an adjacency matrix for each team.

3.4.5. Control variables

Four control variables were included based on prior theoretical and empirical evidence of their relevance for teams’ transactive memory systems: task interdependence, team familiarity, team size, and teamwork experience. *Task interdependence* is indicative of the extent to which individuals’ tasks performance depends on the performance of others. This variable was measured by an item retrieved from Su (2021), which asks respondents to indicate “To what extent the successful completion of your project work depends on the work of each member, and vice versa?”. The item was presented in a peer-rating format on a seven-point scale (1=strongly disagree, 7=strongly agree). *Team familiarity*, which indicates the extent to which individuals knew their teammates before the team project started (Lewis, 2004), was measured by asking participants to indicate “how well do you know your teammates?” on a five-point scale (1=do not know, 5=know very well). This approach has been used in other studies measuring team familiarity in the transactive memory systems’ literature (Lewis, 2004). *Team size* indicated the number of members in the team. *Teamwork experience* measured the incoming individuals’ levels of expertise regarding group collaboration. *Teamwork experience* assessed the extent to which participants worked in teams before the study using three items on a seven-point scale

(1=strongly disagree, 7=strongly agree) adapted from Pazos et al. (2016). A sample item is "I have experience working on team projects as a part of a class". These four variables were used as group-level covariates in the dyadic and group-level models. The description of the items is provided in Appendix A.

3.5 DATA COLLECTION

The data collection procedure included the following steps. First, the participants were informed about the study and invited to participate at the beginning of the team project. Next, they were asked to complete the initial survey during the first month of the collaboration. During the same period, teams' rosters were collected from the instructors to build and distribute the post-project survey. Finally, participants were asked to complete the last survey towards the end of the project conclusion. Both surveys were distributed online using Qualtrics.

The first survey collected data on teamwork experience and team familiarity. The second survey was distributed toward the end of the execution phase to collect data on cognitive conflict, affective conflict, communication quality, expertise retrieval, task interdependence, and the behavioral indicators of transactive memory systems. An additional survey was distributed among the engineering design teams toward the end of the planning phase (first semester) to conduct a complementary reliability analysis.

3.6 DATA ANALYSIS

The data analysis strategy included three main components. First, the measurement scales were examined to provide evidence of reliability and validity. Next, the dyadic-level and group-level variables were computed from the corresponding raw data. Finally, the hypotheses testing was conducted. The data analysis procedures are described below.

3.6.1 Reliability and validity of the measurement scales

The reliability and validity of the measurement scales were examined following the recommendations for positivistic methodologies (Brewer & Sousa-Poza, 2009), and more specifically, for non-experimental research (Mitchell, 1985). Reliability was assessed using coefficients of internal consistency from classical test theory, and evidence of validity was supported in terms of construct and statistical conclusion validity using procedures from the same theoretical framework.

Evidence of reliability

Peer-rating scales. The reliability of peer-rating scales, intrateam conflict, communication, and expertise retrieval, was examined under Generalizability Theory (G-theory). G-theory is a conceptual framework that describes a set of statistical methods to evaluate the psychometric properties of measurements (Brennan, 2003; Huebner & Lucht, 2019). These methods account for multilevel data structures by providing unbiased estimates of reliability when sources of nonindependence or clustered variance are present (Geldhof et al., 2014; Huebner & Lucht, 2019). The framework is an extension of classical test theory as it provides resources to assess the reliability of scales through the analysis of variance components and sources of error (Brennan, 2003).

G-theory was considered an appropriate framework to compute the reliability of the data collected through peer-rating scales. The data structure from peer-rating scales was represented as a two-facet crossed design (*p x i x o*) (Huebner & Lucht, 2019) since all participants completed the same set of items on multiple occasions to assess all their teammates. Hence, the design involved: the person (*p*) answering the item, the item (*i*), and the person being assessed on the item (*o*). For a detailed description of the mathematical computations in G-theory studies, please refer to Brennan (2003).

Following the conventional procedure in G-theory, the data analysis included two elements: a G study to extract the variance components of the measurements, and a D study to estimate the instrument reliability in the form of a generalizability coefficient ($E\rho^2$). This coefficient can be interpreted as a form of standardized interrater reliability (Brennan, 2003). A coefficient ≥ 0.70 was considered acceptable based on recommendations from classical test theory for reliability coefficients (Nunnally, 1994). The analysis was conducted on each scale separately. This analysis was performed on R version 4.2.2 (R Core Team, 2013) using the *gtheory* package (Moore & Moore, 2016).

Self-assessment scales. The Behavioral Indicators of Transactive Memory Systems and teamwork experience scales were distributed in self-assessment formats. This is a traditional way of measuring transactive memory systems since it captures each individual's assessment of knowledge held by others in the team. The reliability of these scales was examined using Cronbach's alpha indexes. Coefficients above 0.70 were considered acceptable (Nunnally, 1994). The analysis was conducted on R version 4.2.2 (R Core Team, 2013) using the *psy* and *sjPlot*.

Evidence of validity

Construct validity. Construct validity is about how well a theoretical construct is captured by the measure (Mitchell, 1985). Previous studies conducted on different samples have provided evidence of construct validity of the intrateam conflict (Behfar et al., 2011), intrateam communication (Peltokorpi & Manka, 2008), and transactive memory systems (Kush, 2019; Lewis, 2003; Todorova, 2020) scales. Nevertheless, factor analysis procedures were necessary because these instruments were modified to fit the study needs by reducing the number of items and/or adapting them to a peer-rating format.

Since the data collected had a nested structure (respondents grouped in teams), a factor analysis procedure for multilevel data was used to provide evidence of construct validity. Multilevel Confirmatory Factor Analysis (MCFA) is a factor analytic framework describing optimal statistical procedures that facilitate the interpretation of factor structures when different levels of measurement are involved (Huang, 2017). For example, data collected at the individual level that is aggregated at the group level may represent constructs with different interpretations depending on the level of analysis (Bliese, 2000). In such cases, MCFA allows accounting for the two-level structure by partitioning the covariance matrix into the within and between variance components (Huang, 2017).

MCFA was used on the measurement scales to estimate an unbiased level-one factor model. The analytic procedure consisted of two separate factor analyses. The first analysis involved the data collected through peer-rating scales. The second analysis tested the factor structure of the self-assessment scales. In each analysis, a one-factor model containing all items was specified and estimated first. Then, its model fit was compared against the fit indexes of the respective theoretical factor model. An acceptable model fit was assumed based on the following values: Comparative Fit Index (*CFI*) ≥ 90, Root Mean Square Error of Approximation (*RMSEA*) ≤ 0.06, and Standardized Root Mean Square Residual (*SRMR*) ≤ 0.08 (Bentler, 1990; Mathieu &

Taylor, 2006). X^2 statistics were also reported. All analyses were conducted on R version 4.2.2 (R Core Team, 2013) using the *lavaan* package (Rosseel, 2012).

Statistical conclusion validity. The reliability of measurement scales is particularly relevant for the proposed cross-sectional research because it may affect the statistical model's test (Mitchell, 1985). The reliability indexes estimated from the scales were deemed acceptable (≥ 0.70) (Nunnally, 1994), which supported the statistical conclusion validity. Scaling and centering procedures were implemented to address potential multicollinearity issues before testing the statistical models. Scaling and centering are recommended to examine data from multiple scales and to test interactions between variables (i.e., moderation) in multilevel models (Field et al., 2012; Finch et al., 2019; Heck & Thomas, 2015), respectively. In sum, this analytic strategy aimed to provide evidence that the measures were appropriate in this study and that the statistical models used to test their relationships were reliable.

Internal and external validity. The proposed study recognizes some limitations. As conceived for experimental research, internal validity can't be fully supported in cross-sectional designs because explanations of causation are not investigated. However, some support can be provided by minimizing the influence of unexpected third variables on a particular relationship (Mitchell, 1985). Additionally, theoretical support was provided to describe the research model. The measurement of four control variables, group size, team familiarity, task interdependence, and teamwork experience, were presumed to mitigate the influence of theoretically relevant third variables on the model (Peltokorpi, 2008). Limitations for external validity were also acknowledged because of the non-random sample and a single setting for hypotheses testing. These limitations could be addressed with future replication studies using different samples.

3.6.2 Construction of variables for hypothesis testing

The computation of variables for hypotheses testing depended upon the instrument used for data collection and the level of analysis at which these variables were used. The specific computation procedures are described below.

Variables from peer-rating scales

The data collected through peer-rating scales were structured into adjacency matrices to estimate dyadic-level variables and indexes of network density for the group-level model. Adjacency matrices were person-by-person tables where the first row and first column list the team members, and cell entries indicate the respective ratings reported in the measurement scales (i.e., communication, cognitive conflict). These matrices were computed for each variable in two steps.

First, peer-rating scores from each item were structured in a non-symmetrized valued adjacency matrix. For instance, consider member *i* and member *j* from team one (*1*) in the adjacency matrix of cognitive conflict (*CC*) item one (*1*). The resulting matrix is CC_{11} = [i_j], where a_{ij} = 7 would indicate that *i* and *j* reported high levels of cognitive conflict in item 1, whereas a_{ij} = 1 would suggest *i* reported an absence of cognitive conflict with *j*. Similarly, a value of a_{ji} = 7 in AC_{11} indicates that member *j* reported high affective conflict with *i*. By considering *i* → *j* and *j* → *i* values, the result is a cell-by-cell directed and valued matrix (Borgatti et al., 2018; Marineau et al., 2018).

Second, matrices from items measuring the same variable were combined to form a single variable matrix. For instance, the adjacency matrix of cognitive conflict (*CC*) of team one (*t1*) was $CCt_1 = CC_{11} + CC_{12} + CC_{13}$, where CC_{11} = item one matrix, CC_{12} = item two matrix,

CC_{13} = item three matrix. Four separated adjacency matrices for each team were generated from this process, representing cognitive conflict, affective conflict, intrateam communication, and expertise retrieval.

Directed dyadic values within the variable matrices were extracted and re-arranged to create a dataset of dyadic-level variables. The dyadic-level values displayed the perceived conflict, communication, and expertise retrieval that each person reported regarding their teammates. For example, dyadic values of communication quality showed who communicated with whom and the perceived quality of that communication. For cognitive and affective conflict, dyadic values represented who perceived conflict with whom and to what intensity. Regarding expertise retrieval, dyadic values captured who retrieved expertise from whom and the frequency of that process.

Furthermore, the variable matrices were imported into a software for network analysis called UCINET (Borgatti et al., 2002) to estimate the group-level density indexes. Network density is a network-level property that indicates the level of within-group connectedness (Borgatti et al., 2002). In valued networks, like those used in this study, weighted density referred to the total of all values in the network associations divided by the sum of all possible ties. The number of possible relations was given by $n(n-1)/2$, where n is the number of team members. The network indexes obtained for each variable were organized in a dataset of group-level variables.

Variables from self-assessment

The data collected through self-assessment scales, the behavioral indicators of transactive memory systems, teamwork experience, and team familiarity were computed in a three-step process to represent group-level variables. First, items measuring the same construct were averaged to generate a single variable value per participant. Second, the variable values of participants from the same team were averaged to obtain group-level variables. Third, r_{wg} indexes were estimated for each group-level variable to justify the data aggregation.

The r_{wg} index was proposed by James et al. (1984) as a method for assessing within-group interrater agreement from single items or a set of items, where values ≤ 70 are considered appropriate to justify aggregation (Maynard et al., 2019). Following the conventional procedure, r_{wg} indexes were estimated for each team. Then, the median values of the indexes corresponding to the same variable were calculated and compared against the cutoff value of 0.70. Once the aggregation was justified, the group-level variables were included in the dataset for analysis.

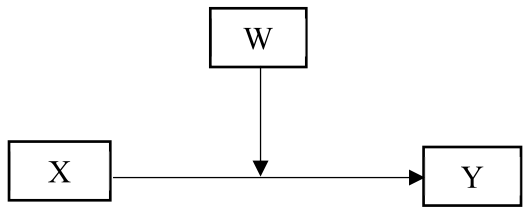
3.6.3 Hypotheses testing

The research hypotheses were tested using moderated moderation models. Moderation analysis was the appropriate analytic approach for hypotheses testing because the interest was to determine the influence of a particular variable on the association between the other two variables (Hayes, 2013).

Moderation is an analytical method used to examine a third variable's effect in statistical models (Jose, 2019). The third variable is the moderator in these models (Hayes, 2013). To illustrate moderation models and the third-variable effect, let's consider the typical example of a simple model with X, Y, and W, where X=independent variable, Y=dependent variable, and W=third variable (Figure 3). Generally speaking, the simple moderation model includes an interaction term between X and W, with no direct relation or causal effect, in which the moderator alters the X-Y relationship.

Figure 3.

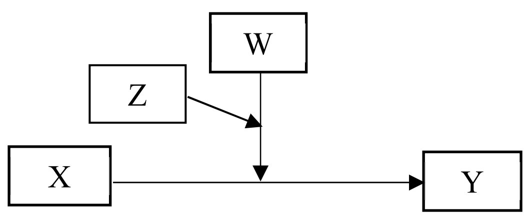
Conceptual diagram of a simple moderation model.



A moderated moderation model uses the simple moderation model as the baseline but incorporates a second moderator (Z) in the interaction between X and the first moderator (W) of the X – Y association. A moderated moderation model with *W* and *Z* is illustrated in Figure 4.

Figure 4.

Conceptual diagram of a moderated moderation model.



The addition of Z creates a three-way interaction term in the regression model. The product of this interaction indicates whether the relationship between X and Y varies at different values of the W x Z interaction. In sum, W moderates the effect of X on Y when the strength of their relationship can be predicted by W, and Z moderates the moderation effect of W when the strength of this moderation effect varies at different values of Z (Hayes, 2013).

The dyadic-level hypotheses were tested using moderated moderation analysis within the mixed-effects models' framework. A mixed-effects model extends the single-level regression model to a multilevel framework to test level-one predictors while accounting for the potential variability in the outcome variable across groups (Raudenbush & Bryk, 2002). Because the dyadic-level variables (Level 1) were clustered in teams (Level 2), the assumption of independence from the traditional Ordinary Least Square (OLS) regression was violated (Heck & Thomas, 2015). Therefore, multilevel regression techniques that account for the nonindependence of observations were required to analyze the relationships between variables (Hayes & Rockwood, 2020).

The multilevel analysis involved three types of models. First, a baseline model (or null model) with random intercepts was used to determine the amount of variance in the dependent variable due to the between-group variance. This variance was computed as an Intraclass Correlation Coefficient (ICC). Next, a means-as-outcomes tested the relationship between the control and response variables. Finally, the dyadic-level predictor variables were sequentially included in the random-intercepts model as fixed effects to examine their relationship with expertise retrieval.

The raw values of the predictor variables were used first in the model. Then, these values were replaced by their centered values. Centering is a procedure recommended in multilevel modeling to facilitate the interpretation of the model coefficients and to mitigate collinearity issues when interaction terms are included (Finch et al., 2019; Heck & Thomas, 2015). All predictor variables were grand mean centered, so the relationships between predictors and the dependent variable were interpreted by comparing dyads across the entire sample rather than within groups (Finch et al., 2019).

The structural and variance components of the multilevel models were estimated using Restricted Maximum-Likelihood estimation (REML). REML is generally recommended for multilevel models because it provides more accurate estimates of variance parameters than Maximum Likelihood estimation (MLE) (Finch et al., 2019) and generates efficient estimates when samples are unbalanced (i.e., different group sizes) (Heck & Thomas, 2015). Multilevel model assumptions, including normality of residuals, uncorrelated residuals, and equal variances across groups (Bickel, 2007) were examined as part of the analysis.

The group-level hypotheses were tested using hierarchical regression models with interaction terms. Regression coefficients and confidence intervals for the independent variables and the interaction terms were used to test the research hypotheses. Because this analysis was based on regression models, assumptions related to linearity, heteroscedasticity, and normality were examined. The hypotheses testing was conducted in R version 4.2.2 (R Core Team, 2013).

3.7 SUMMARY

This chapter re-introduced the study purpose and described the methods to test the research hypotheses. The quantitative design relied on a survey method for data collection and statistical tools for data analysis. Participants in this study included engineering students working on team-based projects. A preliminary power analysis for hierarchical linear models informed the number of participants in the sample. The sample in the study was selected through convenience sampling. The study variables and measurement instruments were also discussed in this section. In addition, a description of the data collection procedure was provided. Finally, the methods of data analysis with emphasis on the evaluation of reliability and validity, and hypotheses testing were presented. The following chapter presents the results of the data analysis.

CHAPTER 4

RESULTS

4.1 INTRODUCTION

This chapter presents the results of the study. The content of the chapter starts with a description of the final sample used for data analysis and hypothesis testing. A subsection presenting reliability and factor analysis results, and interrater agreement results to justify data aggregation are also included here. The last section of the chapter shows the outputs of the dyadic-level and group-level hypotheses testing.

4.2 DESCRIPTION OF THE SAMPLE

Two hundred thirty-eight individuals from 50 teams were invited to participate in the study. A final sample of 189 individuals in 44 teams was retained based on complete data and data consent. The sample combined 23 engineering design projects, and 21 systems analysis and design projects. The team size ranged from 3 to 11 members, with a median of 4 individuals. The sample generated 874 directed dyads.

Most individuals who indicated a gender identified as male (73%), while 25% identified as female. The remaining individuals did not specify a gender. Regarding ethnicity, 64.1% of the sample identified as White or Caucasian, 12.3 % as Black or African American, 10.6% as Asian or Asian Indian, and 9.4% as Hispanic or Latino/a. The remaining sample indicated other minorities or did not specify ethnicity. Regarding education, most individuals in the sample were undergraduate engineering students (67.2%), while 32.8% were graduate engineering students. The participants were from three main disciplines: mechanical engineering (56.6%), engineering technology (13.2%), and engineering management and systems engineering (30.1%).

4.3 MEASUREMENT VALIDATION AND DATA AGGREGATION

4.3.1. Reliability and factor analysis of the scales

Peer-rating scales

The reliability and factor analysis of the intrateam communication (three items), affective conflict (3 items), cognitive conflict (3 items), and expertise retrieval (3 items) scales were examined first. G-studies and Multilevel Confirmatory Factor Analysis (*MCFA*) procedures were conducted on a dataset that contained 10,488 peer-rating records corresponding to 189 respondents. Eight hundred seventy-four directed dyads were present in the peer-rating data. There were no missing values in the dataset. Descriptive statistics of the items grouped by scale are shown in Table 3.

Table 3.

Mean and standard deviation (SD) of the peer-rating items

Scale	Item number	Mean	SD	$E\rho^2$
Intrateam	COM1	6.04	1.24	
communication	COM2	6.10	1.32	0.714
	COM3	6.43	1.04	
Cognitive conflict	CC1	3.61	2.15	
	CC2	4.31	1.98	0.825
	CC3	3.58	2.05	
Affective conflict	AC1	1.17	0.64	
	AC2	1.14	0.57	0.787
	AC3	1.07	0.43	
Expertise retrieval	ER1	4.80	1.91	
	ER2	4.76	1.97	0.842
	ER3	4.58	2.01	

Note. $E\rho^2$ reliability coefficients ≥ 0.70 were deemed acceptable (Nunnally, 1994).

Reliability analysis results. G-studies were performed on the scales separately. All $E\rho^2$ coefficients obtained from the data were acceptable (Table 3).

Factor analysis results. The four peer-rating scales were combined in the MCFA. A one-factor model combining the 12 items was tested first. The model specification used the respondents' team affiliation as the clustering variable. The measures of model fit indicated that the one-factor model fitted the data poorly: X^2 (54) = 890.411, p < 0.01; *RMSEA* = 0.133; *CFI* = 0.484; *SRMR* = 0.186.

A four-factor model to reflect the four variables was expected to fit the data better than a single-factor model. The theoretical four-factor model was estimated with the team affiliation as the clustering variable and then compared to the one-factor model. The measures of model fit showed that the four-factor structure fitted the data well: X^2 (48) = 87.503, p < 0.01; *RMSEA* = 0.031; *CFI* = 0.976; *SRMR* = 0.035. The standard factor loadings of all items were above 0.60.

The statistical comparison between the one-factor and four-factor models proved that the latest fitted the data structure significantly better (Table 4). Therefore, the four-factor structure from the peer-rating scales was confirmed by the MCFA.

Table 4.

Factor model comparison: peer-rating data

Model	CFI	Chi-squared (X^2 standard) difference	Df difference	p-value	Delta CFI
One factor	0.484				
Four factors	0.976	192.76	6	<0.001	0.492

Note. A *p-value* < 0.01 indicates that the X^2 difference is statistically significant.

Self-assessment scales

The reliability and factor analysis of the Behavioral Indicators of Transactive Memory Systems (9 items) and teamwork experience (3 items) scales were examined within the same study. Complete data from 173 individuals' responses representing 44 teams were used for the analysis. Table 5 shows the descriptive statistics of the items.

Table 5.

Mean and standard deviation (SD) of the self-assessment items

Scale	Item number	Mean	SD
Behavioral Indicators of Transactive Memory Systems	TE1	4.07	0.85
	TE2	4.11	0.92
	TE3	4.25	0.75
	TCR1	4.51	0.65
	TCR2	4.39	0.76
	TCR3	4.35	0.79
	TCO1	4.30	0.82
	TCO2	4.07	0.92
	TCO3	4.05	0.92
Teamwork experience	TExp1	6.18	1.08
	TExp2	5.48	1.58
	TExp4	5.54	1.59

A one-factor model combining both scales was tested first. The respondents' team affiliation was used as the clustering variable in the model specification. As expected, the measures of model fit indicated that a one-factor model did not fit the data well: X^2 (54) = 278.516, $p < 0.01$; *RMSEA* = 0.155; *CFI* = 0.625; *SRMR* = 0.110.

Next, the one-factor model was compared against a two-factor model that combined the transactive memory system's items into a single factor. For theoretical reasons, several studies support aggregating these items to represent a high-level transactive memory system's variable (Kush, 2019; Lewis & Herndon, 2011). Finally, a four-factor model was estimated using the team affiliation as the clustering variable, and then compared to the two-factor model. Prior studies have shown that the scale to measure transactive memory systems has a three-factor structure representing three behavioral indicators: task specialization, task credibility, and task coordination (Lewis, 2003). Hence, three lower-level constructs from the transactive memory systems scale and a fourth factor representing teamwork experience were expected from the data.

Results of the analysis showed that the four-factor model fitted the data appropriately, X^2 (48) = 46.427, $p < 0.01$; *RMSEA* = 0.030; *CFI* = 0.991; *SRMR* = 0.041. According to the model comparisons, the four-factor measurement model fitted the data significantly better than the other two models (Table 6).

Table 6.

Factor model comparisons: self-assessment data

Model	Chi-squared (X^2 standard) difference	Df difference	p-value	Delta CFI
One factor vs two-factor	19.384	1	<0.001	0.079
Two-factor vs four-factor	130.36	5	<0.001	0.287

Note. A *p-value* < 0.01 indicates that the X^2 difference between models is statistically significant.

The overall results of the MCFA confirmed the four-factor structure of the data. The model was interpreted in terms of three subconstructs reflecting the behavioral indicators of transactive memory systems, and one teamwork experience construct. The factor loadings of the items were above 0.50, except for one item of the teamwork experience scale with a loading of 0.322 (*TExp4*, "*I have previously used computer-based applications to support remote collaboration*").

The reliability analysis showed acceptable internal consistency of each subconstruct of the transactive memory system's scale (Cronbach's alpha > 0.70). The internal consistency of the whole scale was also acceptable (Cronbach's alpha = 0.861). The reliability coefficient of the teamwork experience scale was below an acceptable value, Cronbach's alpha = 0.577. This index was improved by excluding item *TExp4* (alpha if deleted = 0.70). The exclusion of one problematic item from the teamwork experience scale did not affect the model fit ($X^2_{\text{difference}}$ = 10.495, *p-value* = 0.39; Delta CFI = 0). Thus, only two items of the teamwork experience (*TExp1* and *TExp2*) and nine items of the Behavioral Indicators of Transactive Memory Systems' scales were retained.

4.3.2. Data aggregation for group-level data

Within-group interrater agreement indexes were estimated to justify group-level aggregation for the following scales: Behavioral Indicators of Transactive Memory Systems (median r_{wg} = 0.98), teamwork experience (median r_{wg} = 0.92), and team familiarity (median r_{wg} = 0.72). Based on a reference value of $r_{wg} \geq 0.70$ (Maynard et al., 2019), acceptable levels of agreement were found across the scales.

4.4 TESTING THE RESEARCH HYPOTHESES.

This study hypothesized that cognitive and affective conflicts moderate the association between intrateam communication and transactive memory systems. While a positive moderation effect of cognitive conflict was proposed, affective conflict was considered detrimental by negatively interacting with cognitive conflict. The proposed associations and moderation effects were tested at the dyadic and group levels.

Before proceeding with the analysis, the potential differences in the dyadic and group-level dependent variables due to teams performing different project types (engineering design and systems analysis and design), and differences in individuals' teamwork experience between project types were examined using Analysis of Variance (ANOVA). Results indicated no significant effects of project type on expertise retrieval, $F(1,872) = 4.71$, p-value = 0.06, or the transactive memory system use, $F(1,42) = 0.56$, p-value = 0.45. These results suggested that differences between project types would not affect the results of hypotheses testing. Regarding teamwork experience, an ANCOVA test examined whether the differences in teamwork experience among participants would introduce variance in the response variables. Since teamwork experience was used as a group-level control variable, a team average was estimated from individuals' responses. The results revealed that the group's average teamwork experience was unrelated to expertise retrieval ($\gamma_{01} = 0.298$, p-value = 0.10), or the transactive memory system use ($\beta_1 = 0.032$, *p-value* = 0.63). In sum, there was no evidence to suggest that differences in prior teamwork experience would affect the results.

4.4.1. Dyadic-level model

The dyadic-level hypotheses were tested using multilevel regression models. Descriptive statistics of the study variables and control variables are presented in Table 7. The random-intercept model with no predictors (*Null Model*) was used to estimate the within and between-group variance in the response variable. Significant within-group ($\sigma^2 = 3.12$, p-value < 0.05) and between-group variance components ($\tau_{00} = 0.53$, p-value <0.05) in dyadic expertise retrieval were found. The significant variability between groups suggested that using mixed-effect models was required to obtain level-one unbiased estimates. The *ICC* indicated that 14.6% of the total variance in the dependent variable was due to between-group differences. Results of the null model showed that the grand mean of expertise retrieval (γ_{00}) was 4.60.

Table 7.

Descriptive statistics: dyadic-level variables and group-level control variables

Dyadic-level variables	1	2	3	4
1. Expertise retrieval	_	.429*	.472*	-.136*
2. Communication quality		_	.331*	-.283*
3. Cognitive conflict			_	-.001
4. Affective conflict				_
Mean	4.71	6.19	3.83	1.13
Standard deviation	1.87	1.06	1.87	0.48
Standard error	0.06	0.04	0.06	0.02
N_1	874	874	874	874

Group-level control variables	Task interdependence	Team familiarity	Team size	Teamwork experience
Mean	5.94	1.17	4.64	5.72
Standard deviation	0.99	1.10	2.15	0.82
Standard error	0.15	0.17	0.32	0.12
N_2	44	44	44	44

Note. Correlation coefficients between dyadic-level variables are shown above the diagonal of the upper table. (*) indicates that the correlation is significant at the 0.05 level (2-tailed). N_1 = number of directed dyads; N_2 = number of teams.

A means-as-outcomes model (*Control Model*) assessed the relationships between the four control variables and the dependent variable. This model type was needed since the four variables were used as group-level variables. The four control variables were grand mean centered before adding them into the control model. The results showed no significant regression coefficients in the model. Specifically, task interdependence (γ_{01} = 0.258, *p-value* = 0.14), team familiarity (γ_{02} = 0.013, *p-value* = 0.94), team size (γ_{03} = -0.00, *p-value* = 0.99), and mean teamwork experience (γ_{04} = 0.264, *p-value* = 0.18), were not related to expertise retrieval. The within and between variance components were similar to the null model. A model comparison indicated that adding control variables did not improve the model fit ($X^2_{\text{difference}}$ = 5.69, *p-value* =

0.22). Despite these results, task interdependence and team average teamwork experience were included in subsequent analyses as their regression coefficients were above 0.25.

Hypothesis H_{1a} proposed that as the communication quality of a dyad increased so did expertise retrieval. This hypothesis was tested by including communication quality in the random-intercepts model (*Model 1*). The level-one predictor was grand-mean centered before the analysis. Results of Model 1 fully supported H_{1a} as the regression coefficient was positive and statistically significant ($\gamma_{(com)10}$ = 0.754, *p-value* < 0.01). Results of the variance components suggested that the model explained 19.7% of the within variance in expertise retrieval. Furthermore, Model 1 was better than the null model as the model fit significantly improved ($X^2_{\text{difference}}$ = 170.71, *p-value* < 0.01).

Hypothesis H_{2a} proposed that cognitive conflict positively moderates the relationship between communication quality and expertise retrieval across dyads. The interaction term between communication quality and cognitive conflict was included in a random-intercepts model (*Model 2*). Both predictors were grand-mean centered. The results did not support the hypothesized moderation effect of cognitive conflict ($\gamma_{(com\ x\ cc)30}$ = -0.038, *p-value* < 0.264). Nevertheless, Model 2 significantly improved the model fit ($X^2_{\text{difference}}$ = 142.53, *p-value* < 0.01).

Hypothesis H_{3a} proposed a moderated moderation effect involving the two conflict types. Although the moderation effect of cognitive conflict was not supported in Model 2, a three-way interaction term between communication quality, cognitive conflict, and affective conflict was examined with a random-intercepts model (*Model 3*). The regression coefficient of the three-way interaction was negative and significant ($\gamma_{(com\ x\ cc\ x\ ac)70}$ = -0.124, *p-value* < 0.01), providing some evidence of H_{3a}. The model accounted for 41.3% of the total variance in expertise retrieval. The inclusion of three level-one predictors and their interaction terms significantly improved the model fit ($X^2_{difference}$ = 19.82, *p-value* < 0.01). Table 8 provides the results of all mixed-effects models used for hypotheses testing at the dyadic-level.

Table 8.

Summary of mixed-effects models for hypotheses testing

Fixed effects	Null model	Ctrl. Model	Model 1	Model 2	Model 3
Intercept (γ_{00})	4.606*	4.712*	4.708*	4.798*	4.774*
Communication quality (γ_{10})	-	-	0.754*	0.506*	0.491*
Cognitive conflict (γ_{20})	-	-	-	0.392*	0.367*
Affective conflict (γ_{30})	-	-	-		-0.50*
Communication quality x cognitive conflict (γ_{40})	-	-	-	-0.036	-0.053
Communication quality x affective conflict (γ_{50})	-	-	-	-	-0.26*
Cognitive conflict x affective conflict (γ_{60})	-	-	-	-	-0.35*
Communication quality x cognitive conflict x affective conflict (γ_{70})	-	-	-	-	-0.12*
Task interdependence (γ_{01})	-	0.258	0.069	0.006	-0.002
Team familiarity (γ_{02})	-	0.012	-	-	-
Team size (γ_{03})	-	-0.000	-	-	-
Teamwork experience (γ_{04})	-	0.264	0.212	0.197	0.151
% Total variance explained	-	*14.6%*	*15.4%*	*29.4%*	*41.3%*
$X^2_{difference}$ vs. *previous model*	-	*5.690*	*170.7**	*144.3**	*18.04**

Model	Covariance Component	Estimate	Standard Deviation	Lower C.I	Upper C.I
Null model	Within (σ^2)	3.120	1.766	1.684	1.855
	Between (τ_{00})	0.534	0.730	0.490	1.006
Control model	Within (σ^2)	3.119	1.766	1.684	1.855
	Between (τ_{00})	0.513	0.716	0.420	0.921
Model 1	Within (σ^2)	2.578	1.605	1.530	1.685
	Between (τ_{00})	0.424	0.651	0.407	0.875
Model 2	Within (σ^2)	2.195	1.482	1.410	1.553
	Between (τ_{00})	0.339	0.583	0.366	0.783
Model 3	Within (σ^2)	2.164	1.471	1.397	1.538
	Between (τ_{00})	0.318	0.564	0.352	0.758

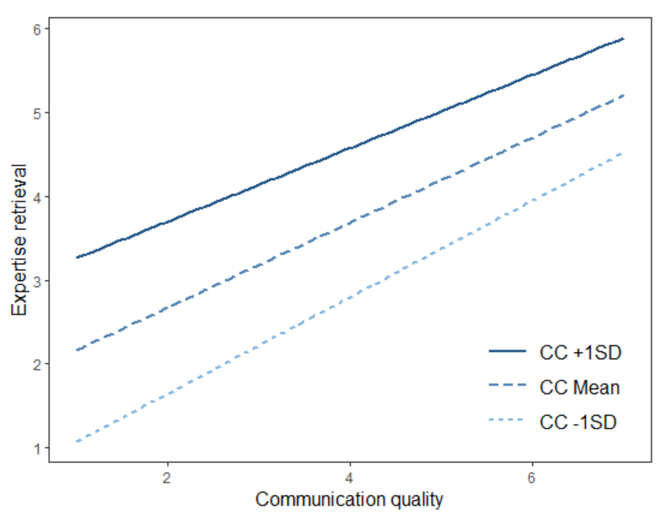
Note. Variables were grand mean centered. (*) Coefficients are significant at 0.05 level. C.I = confidence interval between 2.5% and 97.5%.

Examining the three-way interaction

The results of Model 2 indicated a non-significant moderation effect of cognitive conflict. The interaction term in this model is visually represented in Figure 4. Further, the moderated moderation effect involving cognitive and affective conflicts on the relationship between communication quality and expertise retrieval was supported in Model 3. Nevertheless, the non-significant moderation effect of cognitive conflict ($\gamma_{(com\ x\ cc)40}$ = -0.053, *p-value* = 0.13) and the significant negative interaction between affective conflict and communication ($\gamma_{(com\ x\ ac)50}$ = -0.262, *p-value* = 0.01) from this model suggested that the moderating roles of cognitive and affective conflicts were different than expected. Accordingly, the results of Model 3 suggested that the strength of the moderation effect of affective conflict varied at different values of cognitive conflict. The three-way interaction is shown in Figure 6.

Figure 5.

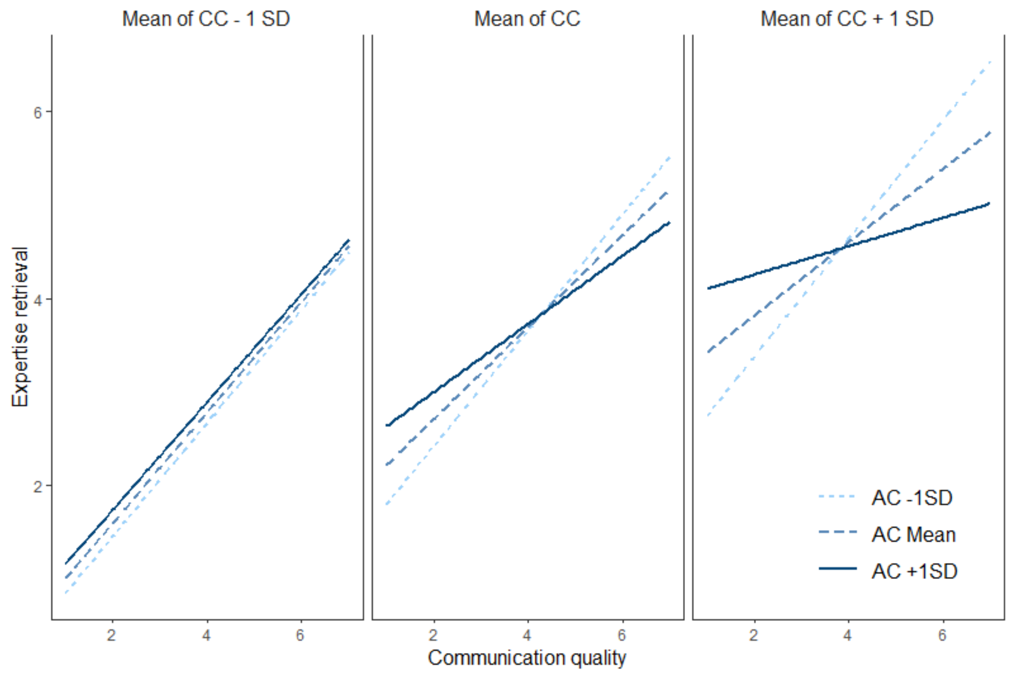
Moderation effect of cognitive conflict on expertise retrieval.



Note. The plot is based on predicted values of the response variable Expertise retrieval. CC = cognitive conflict. Standard deviation (SD) values of the independent variables are displayed in reference to their grand mean.

Figure 6.

Moderated moderation effect on expertise retrieval.



Note. The plot is based on predicted values of the response variable Expertise retrieval. CC = cognitive conflict; AC = affective conflict. Standard deviation (SD) values of the independent variables are displayed in reference to their grand mean.

The interaction effect in Figure 5 shows variations in the slopes of regression lines relating communication quality and expertise retrieval at different cognitive and affective conflict values. The values of the three independent variables were grand-mean centered. The positive slopes of the regression lines were similar when the dyadic affective conflict was one standard deviation below the grand-mean at any values of cognitive conflict. The slope of the regression line was lowered when the dyadic affective conflict was one standard deviation above the grand mean and dyadic cognitive conflict was one standard deviation above the grand mean. In other words, the slope of communication quality decreased when the dyads perceived higher-than-average affective and cognitive conflicts. This indicates that communication has a weaker relation with expertise retrieval in teams with high levels of affective and cognitive conflicts.

The residuals from Model 3 were used to examine the model assumptions visually (Appendix B). Residuals' distribution and Q-Q plots suggested that the normality assumption was not violated despite some minor deviations from the normal line towards the upper tail. The scatterplots between residuals and fitted values showed an even distribution around the line, suggesting a constant variance of residuals.

4.4.2. Group-level model

The group-level hypotheses were tested using hierarchical regression analysis. Descriptive statistics of the study variables and control variables are reported in Table 9.

Table 9.

Descriptive statistics: group-level variables

Variables	1	2	3	4	5	6	7	8
1. TMS use	_	.48*	.49*	-.26	.42*	-.01	.11	.07
2. Communication density		_	.41*	-.11	.41*	.14	.06	.19
3. Cognitive conflict density			_	.05	.33*	.21	.20	.08
4. Affective conflict density				_	.02	-.07	-.09	-.29
5. Task interdependence					_	.38*	.27	.05
6. Team familiarity						_	.66*	.31*
7. Team size							_	.36*
8. Teamwork experience								_
Mean	4.21	6.13	3.52	1.14	5.94	1.17	4.64	5.72
Standard deviation	0.37	0.59	1.01	0.19	0.99	1.10	2.15	0.82
Standard error	0.06	0.09	0.15	0.03	0.15	0.17	0.32	0.12
N	44	44	44	44	44	44	44	44

Note. TMS = Transactive Memory Systems. Correlation coefficients are shown above the diagonal. (*) indicates a significant correlation at the 0.05 level (2-tailed). *N*= number of teams.

An initial regression model (*Control Model*) assessed the relationships between the four control variables and the dependent variable. The results showed a significant regression coefficient for task interdependence (β_{TInd} = 0.188, *p-value* < 0.01) and a marginally significant coefficient for team familiarity (β_{TFam} = -0.121, *p-value* = 0.06). The group mean teamwork experience (β_{TExp} = 0.040, *p-value* = 0.55) was unrelated to the response variable. The control model showed an adjusted R^2 = 0.17; and $F(4,39)$ = 3.306, *p-value* = 0.02. The subsequent analyses included task interdependence and team familiarity as control variables.

Hypothesis H_{1b} proposed that communication quality density was positively associated with the transactive memory system use. The hypothesis was tested by including communication density in the regression model (*Model 1*). The positive regression coefficient of communication density supported H_{1b} (β_{Com} = 0.232, *p-value* = 0.012). Model 1 explained 28.4% of the variance in the dependent variable. A models' comparison suggested that adding communication quality density improved the model ($X^2_{\text{difference}}$ = 5.0392, *p-value* = 0.024).

Hypothesis H_{2b} proposed that cognitive conflict density positively moderates the relationship between communication quality density and the transactive memory system use. The interaction term between communication density and cognitive conflict density was entered into the regression model (*Model 2*). The hypothesized moderation effect of cognitive conflict was not supported (β_{ComxTC} = 0.025, *p-value* = 0.761). Nevertheless, the model comparison suggested that adding the interaction term was worthwhile ($X^2_{\text{difference}}$ = 6.381, *p-value* = 0.041).

The three-way interaction term between communication quality, cognitive conflict, and affective conflict (H_{3b}) was examined in Model 3. Hypothesis H_{3b} regarding the moderated moderation effect at the group-level was not supported ($\beta_{ComxTCxRC}$ = -0.043, *p-value* = 0.978). The specified model increased the adjusted R^2, but the model fit did not improve with the addition of the three-way interaction. Table 10 summarizes the regression models used for hypotheses testing.

Table 10.

Summary of regression models for hypotheses testing

Fixed effects	Ctrl. Model	Model 1	Model 2	Model 3
Intercept	2.849*	2.093*	2.690	9.061
Communication quality (β_{Com})	-	0.232*	0.084	-0.914
Cognitive conflict (β_{CC})	-	-	-0.043	0.370
Affective conflict (β_{AC})	-	-	-	-7.551
Communication quality x cognitive conflict (β_{ComxCC})	-	-	0.025	-0.029
Communication quality x affective conflict (β_{ComxAC})	-	-	-	1.182
Cognitive conflict x affective conflict (β_{CCxAC})	-	-	-	0.227
Communication quality x cognitive conflict x affective conflict ($\beta_{ComxCCxAC}$)	-	-	-	-0.043
Task interdependence (β_{TInd})	0.188*	0.129*	0.115*	0.120*
Team familiarity (β_{TFam})	-0.121	-0.066	-0.077	-0.084
Team size (β_{Size})	0.033	-	-	-
Teamwork experience (β_{TExp})	0.040	-	-	-
Adjusted R^2	*0.176*	*0.284*	*0.348*	*0.403*
$X^2_{\text{difference}}$ vs. *previous model*	-	*5.039**	*6.381**	*8.771*

Note. (*) Coefficients are significant at 0.05 level.

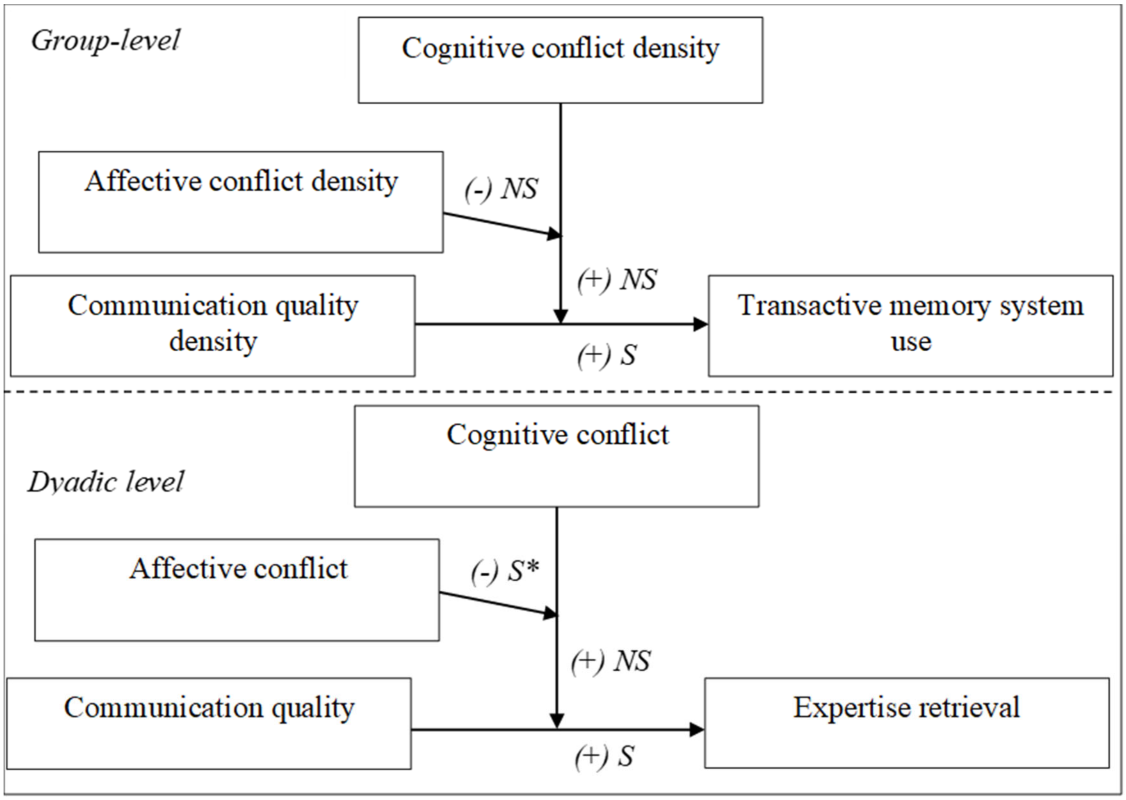
Residuals from Model 2 were used to test the model assumptions. Results suggested that the model fairly met the assumptions (Appendix C).

4.4.3. Summary of hypotheses testing

This study proposed a dyadic-level and a group-level models to test the moderating roles of cognitive and affective conflict on the relationship between communication and teams' transactive memory systems. The results of the hypotheses testing are displayed in Figure 6.

Figure 7.

Summary of hypotheses testing



Note. (-) hypothetical negative relation; (+) hypothetical positive relation. NS = hypothesis was not supported; S = hypothesis was supported; S* = hypothesis was partially supported.

The results fully supported H_{1a} and H_{1b} regarding the positive relationship between communication quality and expertise retrieval and between communication density and the indicators of transactive memory system use, respectively. These results indicated that the quality in which group members communicate was a strong predictor of the extent to which they build trust in one another's capabilities, coordinate their actions, and exchange information and knowledge for task completion.

The hypothesized positive moderation effect of cognitive conflict on the association between communication and transactive memory systems was neither supported at the dyadic

(H_{2a}) nor at the group level (H_{2b}). These results suggested that the amount of group members' disagreements related to the task's content and outcomes is not likely to strengthen the relationship between communication quality and transactive memory systems. What emerged from the analysis of dyads was a direct relationship between cognitive conflict and expertise retrieval, which suggested that the amount of perceived task-related disagreements is a positive predictor of the extent to which group members exchange knowledge for goal attainment.

The hypothesized moderated moderation effect that involved affective conflict, cognitive conflict, and communication quality was partially supported at the dyadic level (H_{3a}), and it was not supported at the group-level (H_{3a}). The analysis related to H_{3a} showed a negative and significant three-way interaction, but the single moderation effect of cognitive conflict was not statistically significant. This result was further examined to understand better the specific roles of cognitive and affective conflicts in the three-way interaction. It was found that the higher the perceived affective conflict in dyads that also perceived high cognitive conflict, the weaker the relationship between communication quality and expertise retrieval. Further, the results indicated that affective conflict was the primary moderator, while cognitive conflict strengthened the negative moderation effect of affective conflict. In sum, the findings regarding the interaction between the two conflict types and communication suggested that the functional role of communication quality in transactive memory system deteriorates when dyads highly engage in both task-related and interpersonal disagreements. In this interaction, affective conflict played a more important role than cognitive conflict in shaping the association between communication and expertise retrieval, though this role was detrimental.

4.5 ADDITIONAL ANALYSIS

An additional analysis was conducted to examine potential differences in the dyadic level study variables due to the demographic characteristics of the sample. The data on gender and ethnicity were used as level-one variables. Gender and ethnicity were coded to show whether individuals in the dyads shared the same gender/ethnicity. For example, gender similarity was 0=different gender and 1=similar gender. Regarding gender, 418 dyads were coded as similar, and 253 dyads were coded as different. Regarding ethnicity, 315 dyads were coded as similar and 352 as distinct.

Results of the analysis using multilevel models indicated that gender similarity was not related significantly to any of the variables. Ethnicity similarity was positively associated with expertise retrieval ($\gamma_{(eth)20}$ = 0.284, *p-value* = 0.049), dyadic cognitive conflict ($\gamma_{(eth)20}$ = 0.322, *p-value* = 0.022), and marginally with communication quality ($\gamma_{(eth)20}$ = 0.158, *p-value* = 0.056). Altogether, the positive coefficients suggested that individuals with similar ethnical backgrounds were more likely to exchange information and ideas about the task than those who differed in terms of ethnicity.

4.6 SUMMARY

This chapter reported the results of data analysis and statistical tests. A description of the sample was provided at the beginning of the chapter. This was followed by the reliability and factor analysis of the peer-rating and self-assessment scales. Results supported the acceptable psychometric properties of the measurement scales used in this study. Furthermore, the estimated indexes of within-group interrater agreement justified the data aggregation from self-assessment scales. The last section of the chapter reported the results of the hypotheses testing. The analysis of the dyadic-level model provided support for H_{1a} and partially for H_{3a}. A further examination of the three-way interaction showed that the interaction between cognitive conflict and affective conflict negatively modified the slope relating communication quality and expertise retrieval. The analysis of the group-level model provided support for H_{1b}, but the hypothesized moderation effect of cognitive conflict (H_{2b}) and the three-way interaction term (H_{3b}) were not supported. These results are discussed further in the next chapter.

CHAPTER 5

CONCLUSIONS AND RECOMMENDATIONS

5.1 INTRODUCTION

This chapter discusses the results reported in the preceding chapter. Chapter 5 begins with a summary of the study that restates the purpose and structure of the research project. A discussion of the findings organized by research questions and the contributions and implications are presented next. The last two sections contain the recommendations for future research, and the conclusions from the findings, respectively.

5.2 SUMMARY OF THE STUDY

The present study approached three research opportunities identified in the literature of team cognition. First, it aimed to increase our understanding of the interplay between intrateam conflict types and communication quality in predicting transactive memory systems' use in engineering teams. Second, it adopted a two-level perspective to investigate the group and dyadic-level theoretical components of transactive memory systems, which has received little attention in the literature. Third, the research design relied on a network-based approach to capture the emergence of the study variables that the most common compositional methods overlook, as team members might relate, interact, and organize with others differently at the dyadic level.

The research project aimed to evaluate a theoretical model that related intrateam communication to transactive memory systems and placed the emergent cognitive and affective conflicts as moderators in this relationship. The research hypotheses about the relationships among the study variables at the dyadic and group levels were built upon the information processing theory and the literature on team cognition. The research hypotheses were quantitatively tested using data from a sample of engineering project teams through previously validated measurement instruments.

The study sample included 189 individuals working in 44 teams. The sample included teams performing engineering design projects and systems analysis and design projects. The team size ranged from 3 to 11 members, with a median of 4 individuals. The participants were asked to complete a set of items from previously developed scales to measure intrateam conflict, communication, expertise retrieval, and transactive memory systems. Additional data on task interdependence, team familiarity, and teamwork experience were collected as control variables. The measurement scales were adapted to the study needs, and therefore, their reliability and construct validity were re-assessed.

The research hypotheses were tested using statistical techniques. Since the data had a nested structure, the dyadic-level model was examined under the mixed-effects models' framework. The group-level model was examined using hierarchical regression models. Additional analysis was conducted to clarify the moderated moderation effect at the dyadic level and to explore potential differences due to the demographic characteristics of the sample. The study results from the data analysis are discussed next.

5.3 DISCUSSION OF THE FINDINGS

Previous studies revealed key factors that enhance the development and operation of transactive memory systems in various types of teams (Bachrach et al., 2019; Lewis, 2004; Palazzolo et al., 2006; Peltokorpi, 2008; Pulles et al., 2017). The present study examined the role of emergent conflict that occurs naturally in the collaboration process in predicting the transactive memory system use in engineering project teams. This section discusses the findings in relation to the three research questions and the two-level hypothesized model.

Research question one:

How does intrateam communication relate to transactive memory systems at the dyadic and group levels? The findings associated with research question one indicated a positive and significant relationship between communication quality and the transactive memory systems components in the sample of engineering project teams. The results showed that perceived communication quality within dyads is a positive predictor of expertise retrieval, such that the higher the perceived quality, the more frequently individuals retrieve task-relevant information and knowledge from others. Similarly, communication quality at the group-level was a positive predictor of the transactive memory system use, such that teams with higher levels of task specialization, task credibility, and task coordination are characterized by a dense communication network.

The study findings regarding research question one support the growing empirical evidence about the relevance of intrateam communication for the operation of the teams' transactive memory systems as it allows members to recognize each other's skills and knowledge, rely on one another for task-knowledge base, coordinate their interdependent actions, and frequently retrieve information from others when needed (Hollingshead & Brandon, 2010; Pulles et al., 2017; Yan et al., 2021). The finding also extends the knowledge base on communication networks and team cognition by suggesting that besides the frequency of interactions (Argote et al., 2018; Su, 2021; Yuan, Carboni, et al., 2010), open and direct communication are crucial attributes that contribute to the operation of the transactive memory systems in engineering project teams.

Research question two:

Does the relationship between intrateam communication and transactive memory systems at the dyadic and group level vary based on cognitive conflict? If so, how? There was no evidence to conclude that the perceived cognitive conflict in the sample of engineering project teams moderated the relationship between intrateam communication and transactive memory systems. The results of the analysis assessing the moderation effect of cognitive conflict showed that the positive slope of perceived communication quality in relation to expertise retrieval within dyads did not vary significantly at different values of cognitive conflict. Similar results were found at the group-level, where the interaction between communication quality density and cognitive conflict was not significant in relation to the transactive memory system use.

These study findings did not align with the expectation that cognitive conflict would shape the information flow (Gibson, 2001; Staw et al., 1981) by strengthening the benefits of intrateam communication for transactive memory systems. Nevertheless, the results of the dyadic-level model placed the emergent cognitive conflict in a primary role worth mentioning. While cognitive conflict was not a significant moderator variable, it directly predicted expertise retrieval. The positive regression coefficient in the model indicated that the more individuals are exposed to divergent ideas and viewpoints related to the task content and outcomes, the more frequently they would retrieve task-relevant information and knowledge from those who expressed different preferences. The observed role of cognitive conflict is similar to a previous study by Humphrey et al. (2017), who based on the study of 51 project teams found that the cognitive conflict perceived in dyads had a positive association with information exchange and team performance. In sum, the results suggested that dyadic cognitive conflict directly contributes to expertise retrieval by allowing individuals to understand each other's opinions, preferences, ideas, and rely on that understanding for further information retrieval during task execution.

Research question three:

Does affective conflict interact with cognitive conflict in shaping the relationship between intrateam communication and transactive memory systems at the dyadic and group levels? If so, how? The analyses in relation to research question three provided different results for the dyadic and group-level models. The findings from the mixed-effects model revealed a negative and significant three-way interaction term involving cognitive conflict, affective conflict, and communication quality in predicting expertise retrieval. The significant regression coefficient from the statistical model suggested that the relationship between communication quality and expertise retrieval varied at different values of the interaction between affective and cognitive conflicts. Further examination of the three-way interaction revealed that when dyads perceived higher-than-average affective conflict while the perceived cognitive conflict was equal to or above the average, the strength of the relationship between communication quality and dyadic expertise retrieval was reduced. This finding showed that affective conflict had negative connotations for team cognition since even a slight increase in interpersonal disagreements or tensions could diminish the benefits of perceived communication quality.

The result contributes to the knowledge base about the role of cognitive and affective conflicts in team cognition in two ways. First, it supports the disruptive effects of affective conflict for transactive memory systems theorized in previous studies. It has been argued that affective conflict can make group members less likely to gain comfort from others (Hu et al., 2019), less receptive to others' ideas regarding the tasks (Todorova, 2020), and less engaged with exchanging ideas (Labianca & Brass, 2006; Sparrowe et al., 2001). Second, it uncovers the relevance of investigating the natural co-occurrence of cognitive and affective conflicts to understand better the repercussions of different conflict profiles on teams' information processing and knowledge use (Bradley et al., 2015; Marineau et al., 2018).

The regression model results showed a non-significant interaction between cognitive and affective conflicts in predicting the transactive memory system use at the group level. This study theorized that the benefits of cognitive conflict for transactive memory systems are mostly perceived under low levels of affective conflict. In line with previous work from an information processing perspective (i.e., Bradley et al., 2015; De Wit et al., 2012; Pazos et al., 2022), it was argued that high interpersonal incompatibilities overuse teams' cognitive resources and detriment the teams' capacity for developing a shared transactive memory. Nevertheless, including the two conflict types in the model did not contribute to explaining the variation in the transactive memory system use in the engineering project teams. Although the co-occurrence of cognitive and affective conflict concerning transactive processes has been examined and supported using a network lens at the dyadic level (i.e., Marineau et al., 2018), the mechanisms by which the network-level structural properties interact remain unclear. It is possible that the unexpected result is due to some aspects of the design such as the sample size. Finding moderation effects is often challenged by the number of moderators tested and their range of values, and these challenges are susceptible to the sample size (MacKinnon, 2011). Such challenges were not likely to interfere with the dyadic-level model as the predictor and moderator variables were included as level-one variables, and group-level moderators were not required. It is also possible that the interaction between conflict types and communication quality is more noticeable in dyads because there is greater variability at this level. This variability arises from individuals experiencing different degrees of conflict with their teammates, depending on the intensity of their interaction. In this scenario, adopting a multilevel perspective when studying emerging conflicts and their impact on team cognition becomes essential.

5.4 CONTRIBUTIONS AND IMPLICATIONS

Modern teams bring together individuals with diverse skills, knowledge, and experiences to accomplish complex tasks that individuals cannot complete alone. When combined effectively, the variety of resources in a team can support key collaboration processes such as idea generation, problem-solving, and decision-making. The divergent perspectives, ideas, and values often present in a team can also lead to disagreements. Understanding how the emergent conflict due to task-related or interpersonal disagreements influences team cognition becomes critical so that the diverse knowledge and skills that reside in each team member can be used as an advantage to enhance group performance.

This study offers insights for managers of engineering teams about the roles of cognitive and affective conflicts in relation to team cognition. The study findings add to the literature on team cognition by providing evidence about the importance of communication quality and the negative influence of affective conflict in developing transactive memory systems. Such findings can be used in practice to identify communication inefficiencies and set targets for team training to promote open and direct communication within the team. Although managers make substantial efforts to prompt the exchange of information and expertise, there are still instances that make individuals less engaged in knowledge-based interactions (Su, 2021), thus affecting the development of transactive memory systems. Furthermore, the study findings can inform conflict management strategies to mitigate the effects of interpersonal conflicts. By considering the specific patterns of conflicts within dyads, it becomes feasible to determine when strategies targeting individuals or dyads involved are more suitable than those addressing conflict at the group-level. Managers need to be able to deal with the emergence of negative relations and intervene before they become a threat to the team.

This study provides valuable methodological and theoretical insights for scholars studying teams and team cognition. First, the measurement and analytic tools described in this study were suitable to examine the structural properties of intrateam conflict and communication and their emergence from the dyadic-level component. The acceptable levels of reliability of the peer-rating scales contribute to the ongoing efforts to provide psychometrically sound and shorter data collection tools to study teams from an organizing and relational perspective (Humphrey & Aime, 2014; Park, Mathieu, et al., 2020). Second, while extending the literature regarding the predictors of transactive memory systems, the study provides empirical evidence on how hindrance relations, such as affective conflict, may disrupt their development and functioning by preventing members from engaging in transactive processes. This research stream has received scant attention in the literature on transactive memory systems. Third, given its precise relationship with performance, insights can be added to the discussion about the role of cognitive and affective conflicts on proximal determinants of project teams' effectiveness.

Finally, some additional insights were added to the literature regarding the contributors of team cognition in engineering project teams beyond those included in the research questions. In line with past studies, the perceived task interdependence was highly relevant for transactive memory systems at the group level since it explained most of the variance in the composite of task credibility, coordination, and expertise recognition. This result shows that functional relationships and dependencies are primary determinants of developing shared transactive memories in teams. This study also provides interesting findings regarding the role of team size in the development of team cognition. Some scholars argued that as more members are included in a team, the communicative capacity is challenged because reaching out to every member becomes difficult for larger teams (Hood et al., 2014; Peltokorpi & Hood, 2019). Since communication is critical for the development and functioning of transactive memory systems, it could be argued that group size is negatively related to transactive memory systems. The results obtained from the sample of engineering project teams, which ranged from 3 to 11 members, suggested that the team size did not play a critical role in predicting the transactive memory systems components.

5.5 LIMITATIONS AND FUTURE RESEARCH

This study aimed to investigate how cognitive and affective conflicts influence intrateam communication and shape the transactive memory system and expertise retrieval of engineering project teams. The findings presented in this study should be taken in light of certain design limitations. First, the measurement method used to characterize the response variable leads to a proximal indicator of expertise retrieval as it does not capture the actual retrieval processes. This study relied on an existing measurement procedure and assessed the psychometric properties of the scale to support construct validity and approach this limitation. Future studies can use this scale in combination with other measurement methods of knowledge-based transactive processes (i.e., Kush et al., 2023; Wagner, 2014) to extend the study findings to other forms of cognition.

Second, the convenient sample of student teams might raise questions regarding the generalizability of findings to organizational project teams. Student-based samples inherently display differences in terms of context and motivation when compared to teams working in professional settings. Nevertheless, past studies have demonstrated that using study settings that approximate professional contexts can help mitigating these limitations (Hood et al., 2017; Lewis, 2004; Todorova, 2020). The study sample displayed many proxies for professional contexts including design projects that approached real-world problems, tools to facilitate virtual collaboration and communication, constituents that act as clients or stakeholders, and time constraints. Furthermore, the sampling procedure was convenient for this study as it allowed controlling for potential confounder variables such as organizational incentives and other pre-existing team-level differences such as team tenure, which otherwise might have influenced our results. The teams are often newly formed, and they had similar requirements for interdependent work driven by weighted group rewards over individual rewards. In sum, the characteristics of the sample were expected to increase the external validity of the findings. Subsequent studies might strengthen the generalizability by examining random samples of work teams or teams performing other types of projects.

Third, the study relied on a two-period time-lag design to collect data regarding the control and study variables. This approach mitigates issues related to common retrieval cues by placing a temporal separation between the measure of predictor variables and the dependent variable (Podsakoff et al., 2012). Although this approach has advantages over cross-sectional designs, it still has some limitations regarding causality. The proposed statistical model was supported using a theoretical framework from information processing theory to increase internal validity and included theoretically relevant variables as covariates to account for alternative causal links. A longitudinal design might be used in future studies to account for the temporal precedence in examining the role of conflict types in the relationship between communication and transactive memory systems over time.

5.6 CONCLUSIONS

This study examined the role of communication quality, cognitive conflict, and affective conflict in the operation of transactive memory systems in the context of engineering project teams. This investigation demonstrated that communication quality enabled retrieval processes and the transactive memory structure. Communication high in openness, directedness, and frequency was a central predictor of the extent to which a pair of members retrieved expertise during project execution. Further, a group communication structure characterized by dense communication channels was highly relevant for building trust, task coordination, and expertise recognition. The examination of the interplay between cognitive and affective conflicts revealed that even a slight increase in interpersonal disagreements between pairs of members diminished the benefits of communication quality on the transactive memory system use. This study expects to add some clarity about the influence of emergent conflict on intrateam communication and transactive memory systems as a critical step to optimizing team functioning.

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APPENDICES

APPENDIX A: SURVEY ITEMS

Communication quality (1=strongly disagree, 7=strongly agree)
1. COM1. I communicate frequently with [X]
2. COM2. I communicate directly with [X]
3. COM3. I can speak openly and freely with [X]

Cognitive conflict (1=none/not at all, 7=always/totally)
1. CC1. To what extend does [X] and you argue the pros and cons of different opinions?
2. CC2. How often does [X] and you discuss evidence for alternative viewpoints?
3. CC3. How often does [X] and you engage in debate about different opinions or ideas?

Affective conflict (1=none/not at all, 7=always/totally)
1. AC1. How much friction is there between you and [X]?
2. AC2. How much are personality conflicts evident between you and [X]?
3. AC3. How much emotional conflict is there between you and [X]?

Expertise retrieval (1=very infrequently, 7=very frequently)
1. ER1. How frequently has [X] provided you information or knowledge that you would need to do your job?
2. ER2. How often have you turned to this person for information or knowledge on project-related topics?
3. ER3. How often has this member provided you information or knowledge that you would need to accomplish your tasks?

Behavioral Indicators of TMS (1=strongly disagree, 5=strongly agree)
1. S1. Each team member has specialized knowledge of some aspect of our project.
2. S2. The specialized knowledge of different team members was needed to complete the project deliverables.
3. S3. I know which team members have expertise in specific areas.
4. CR1. I was comfortable accepting procedural suggestions from other team members.
5. CR2. I trusted that other members' knowledge about the project was credible.
6. CR3. I was confident relying on the information that other team members brought to the discussion.
7. COO1. Our team worked together in a well-coordinated fashion.
8. COO2. Our team had very few misunderstandings about what to do.
9. COO3. We accomplished the task smoothly and efficiently.

Task interdependence (1=strongly disagree, 7=strongly agree)

1. Tind1. The successful completion of our project work depends on the work of [X].

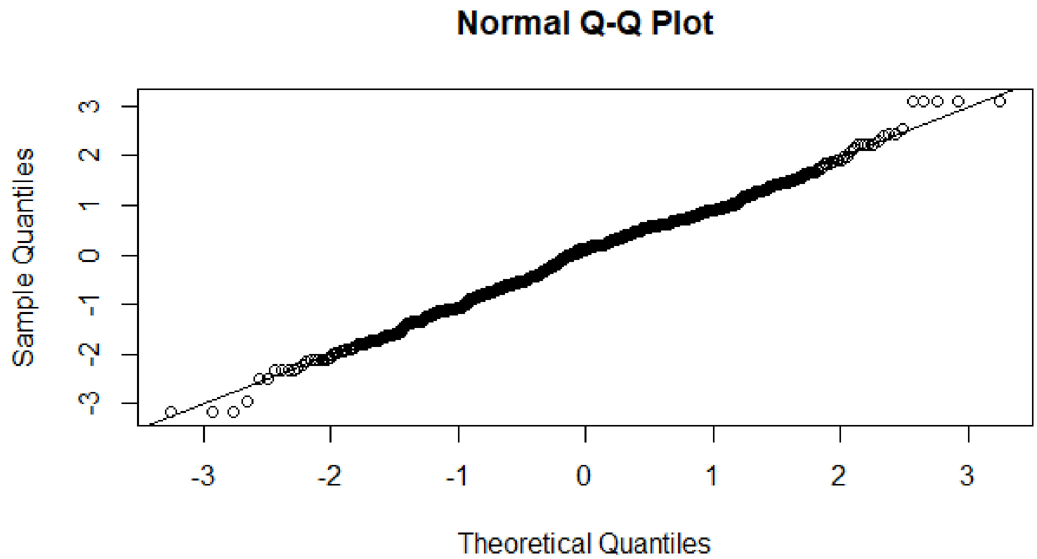
Team familiarity (1=do not know, 5=know very well)

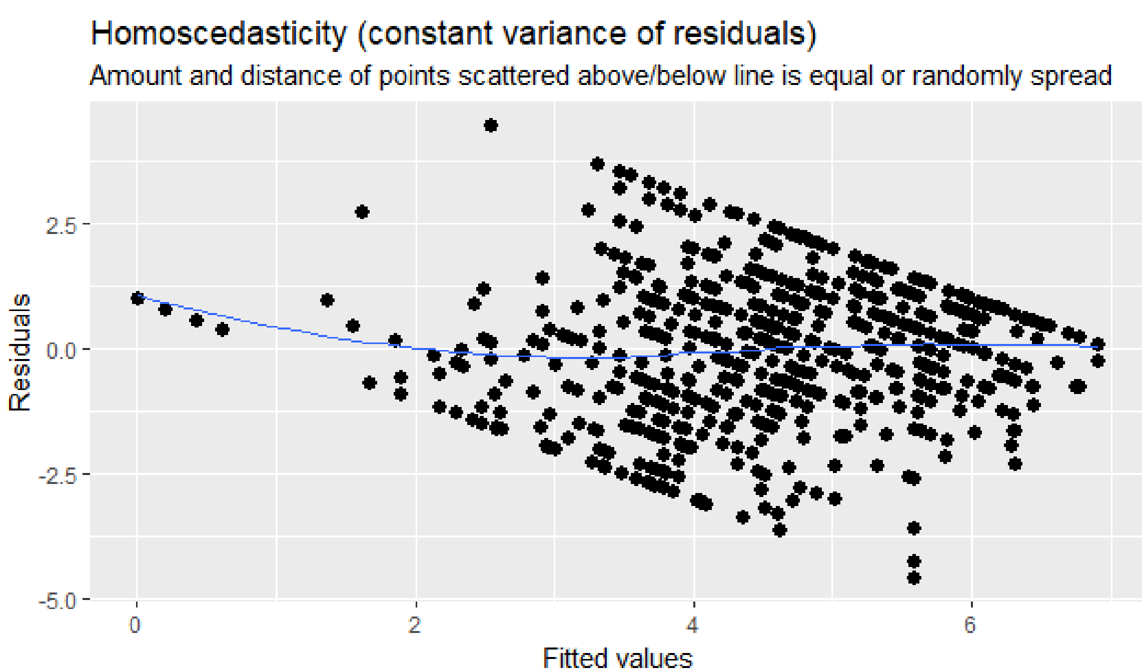
1. TF1. How well do you know your teammates?

Teamwork experience (1=strongly disagree, 7=strongly agree)

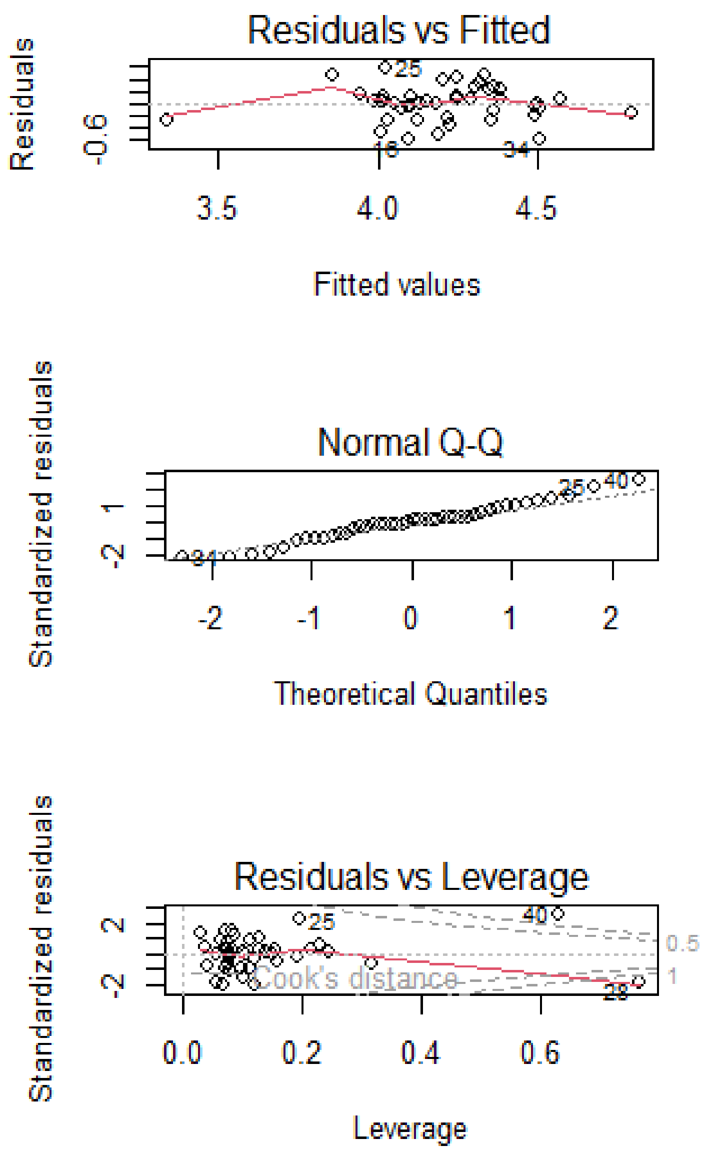
1. TExp1. I have experience working on team projects as a part of a class.
2. TExp2. I have experience working on virtual team projects for classes.
3. TExp3. I have previously used computer-based applications to support remote collaboration.

APPENDIX B: DYADIC-LEVEL MODEL RESIDUAL PLOTS





APPENDIX C: GROUP-LEVEL MODEL RESIDUALS PLOT



APPENDIX D: IRB EXEMPTION

OLD DOMINION UNIVERSITY

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OFFICE OF THE VICE PRESIDENT FOR RESEARCH

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DATE:	April 2, 2021
TO:	Pilar Pazos, Dr.
FROM:	Old Dominion University Engineering Human Subjects Review Committee
PROJECT TITLE:	[1705606-2] Information Sharing influence on Transactive Memory Systems and the mediating role of Conflict States
REFERENCE #:	
SUBMISSION TYPE:	Response/Follow-Up
ACTION:	DETERMINATION OF EXEMPT STATUS
DECISION DATE:	April 2, 2021
REVIEW CATEGORY:	Exemption category #2

Thank you for your submission of Response/Follow-Up materials for this project. The Old Dominion University Engineering Human Subjects Review Committee has determined this project is EXEMPT FROM IRB REVIEW according to federal regulations.

We will retain a copy of this correspondence within our records.

If you have any questions, please contact Stacie Ringleb at 757-683-6363 or sringleb@odu.edu. Please include your project title and reference number in all correspondence with this committee.

This letter has been electronically signed in accordance with all applicable regulations, and a copy is retained within Old Dominion University Engineering Human Subjects Review Committee's records.

VITA

Francisco Cima

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Education
May 2024: Ph.D. in Engineering Management and Systems Engineering. Old Dominion University, Norfolk, Virginia.

September 2017. M.S. Business Planning and Regional Development. Instituto Tecnológico de Mérida, Yucatán, Mex.

August 2013: B.S. Business Management Engineering. Instituto Tecnológico de Tizimin, Yucatán, Mex.

Teaching Experience
August 2022 – December 2022: Instructor of Record. Engineering Economics (ENMA302). Department of Engineering Management and Systems Engineering, Old Dominion University. Norfolk, VA.

January 2019 – May 2021: Virtual Instructor. Statistical Quality Control (MSG-114-319) / Management and Prevention of Job Risks (MSG-212-219). Master of Science in Management of Integrated Quality and Industrial Safety Systems. Universidad Virtual. Estado de Chile.

Recent publications
Pazos, P., Cima, F. (2023). Enablers and barriers of effective communication in virtual engineering teams: the role of teamwork skills and emergent conflict. Proceedings of the Industrial and Systems Engineering Annual Conference (IISE).

Pazos, P., Cima, F., Kidd, J., Gutierrez, K., Faulkner, D., and Lee, M. (2023). Using Cross-Disciplinary Teams to Drive Preservice Teachers' Intention to Integrate Engineering. International Journal of Engineering Education (IJEE), 39(2), 441-452.

Cima, F., Pazos, P. and Canto, A. (2021). The technology transfer network dynamic in the Information Technology Industry of Yucatan, Mexico. Proceedings of the Industrial and Systems Engineering Annual Conference (IISE).

The word processor for this dissertation was Francisco Cima.