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Generalizable Communication Styles in Novice and Expert Team Performance

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Generalizable Communication Styles in Novice and Expert Team Performance

DISSERTATION

submitted in partial satisfaction of the requirements
for the degree of

DOCTOR OF PHILOSOPHY

in Informatics

by

Jason G. Reitman

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DEDICATION

To

Frieda, Julie, Marion, and Harry, who loved learning.

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VITA

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ABSTRACT OF THE DISSERTATION

Generalizable Communication Styles in Novice and Expert Team Performance

By

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Doctor of Philosophy in Informatics

University of California, Irvine, 2022

Professor Constance Steinkuehler, Chair

Much of team communication is a trained process for teams in high pressure environments, like the highly regimented checklists that structure aircraft takeoff and landing. Elite esports teams use communication to maintain tight coordination in the face of chaotic and stressful stimuli, closely resembling behavior of high performing teams in domains seemingly dissimilar from competitive video games. This 2 x 2 factorial design explores differences between in-game communications in *League of Legends* teams that vary in both experience as a team and expertise with the game. The findings describe how content, style, and amount of communication differ between novice and expert teams; whether those differences relate to experience with the game, experience as a team, or both; and whether differences in communication relate to team performance under pressure. This work demonstrates methods that can be built on to explore whether these same communication patterns and solutions can effectively transfer across domains in the interest of training for safety and performance in higher consequence contexts.

Chapter 1

Introduction

In the fall quarter of 2016, the University of California, Irvine (UCI) varsity *League of Legends* (LoL) [42] team held its first practice. That first season they won the West Conference playoffs. The next season they were national champions [33]. That same fall, I began my first year as a UCI Informatics Ph. D. student. Over the next six years, I was lucky enough to witness some of the best performing teams in their respective domains practice their crafts and perform under pressure. I got to watch and participate in the formation and development of new teams, which through failure, perseverance, and practice grew into high performing collectives. They range from world-class lab groups learning what it means to create knowledge together, to the campus's first women's saber fencing squad in years – who I was fortunate enough to coach to an eventual first place finish in the 2018-2019 season of the Intercollegiate Fencing Conference of Southern California [63][1] – to one of the first collegiate scholarship esports teams in the world. These teams worked in wildly different domains. They performed different tasks toward different goals under different pressures on different time scales. They used different leadership structures and assigned team members to different roles. They talked differently. But they all talked. Through face-to-face meetings, emails,

[1] I am proud enough of this to cite the archive where interested readers can find these results.

and all genres of media, each of these teams communicated to strategize, to coordinate, and to improve at their respective craft.

In Sebanz, Bekkering, and Knoblich's [103] words, "the ability to coordinate our actions with those of others is crucial for our success as individuals and as a species." As work and play increasingly happen in synchronous online teams, the potential for coordinated action is growing. Understanding what our teammates are doing, thinking, and attending to at any given moment, though, is harder when teammates are working through digital networks as opposed to face-to-face [91].

The first project I was assigned as a new graduate student was to preform a case study of that varsity LoL team in its first year. My instructions were simply to observe and take notes. I had an incredible amount of freedom. My weekly observations of those former and future professional players developing into one of the best collegiate teams in the nation grew into a line of inquiry first around elite team gameplay and later around team cognition more broadly. The findings from that case study focused on how that team communicated to distribute knowledge and cognitive work in highly competitive LoL play [96]. The methods I developed for the novel study reported on in chapter 4 are developed with the intent to allow study of team communication across domains. This work analyzes competitive LoL play towards two ends: (1) to contribute this context to the broader teams research literature and (2) to demonstrate the effectiveness of this methodology for describing team communication according to the characteristics outlined by prevailing frameworks of team cognition.

1.1 Guiding Questions

The goals of this dissertation are concerned with team communication's role in team performance and team development with methods that can apply to teams across domains to pursue more generalizable team cognition research. In light of those goals the questions guiding this work are two-fold:

1. How do teams communicate to perform in high pressure situations?
2. What differences exist between how expert and novice teams communicate under pressure?

1.2 Research Approach

The empirical study presented in this thesis was conceived after years of observations and interviews with elite and near-elite esports players, coaches, and support staff (e.g. [96, 98, 109]). While conducting that research, I was also reading and reviewing research around computer supported cooperative work, team cognition, peer mentoring, and games for learning.

In the team science literature, there are a number of taxonomies that researchers developed to categorize teams by domain, task type, structure, or any of a number of other characteristics (e.g. [70, 102, 25, 111]). There are also intervention studies that ask a team in one domain to adopt practices from another domain (e.g. [13, 38, 101]). The taxonomies, however, are not built on findings from generalizable, empirical, cross-domain studies, and the interventions are not framed in terms of existing taxonomies. This paradox means that findings from rigorous studies have no bearing on design, training, or practice of teams with similar characteristics or under similar pressures that can, apparently, learn from each other, even if they work on different tasks in different domains.

While the study detailed in chapter 4 focuses on team communication in *League of Legends* [42] (LoL), the methods were purposefully designed to be useful for studying teams across domains toward a generalizable understanding of team communication and cognition under pressure. These methods aim to support more work toward taxonomic theory rooted in empirical data, allowing teams in disparate domains to share knowledge in pursuit of safety and performance. The aim of designing and using methods that can be implemented across domains is to work toward implications for research, design, and training.

1.3 Dissertation Overview

This first chapter provides an introduction to the context, high level research questions, and goals guiding this work. Chapter 2 provides background information and related research upon which this dissertation's theoretical and empirical work stands. Chapter 3 describes LoL play and the requisite teamwork, communication, and expertise required for the tasks inherent in elite competitive performance. Chapter 4 reports on a novel empirical study. This study is designed both to present a methodology that researchers can use to work toward rigorous, generalizable team science and to produce findings and discussion that advance ongoing conversations in the literature regarding the role of different kinds of team communication and expertise in team cognitive performance. Chapter 5 explicates the kinds of teams and teamwork that these data might generalize to and the theoretical arguments for future work with the methods described in chapter 4. Chapter 6 concludes this dissertation with summary discussion.

Chapter 2

Background & Related Work

2.1 Team Cognition

The first of the following two definitions describes team cognition by what it is. The second defines team cognition mostly by what it is not. Together they provide a complete picture of what the study of team cognition is trying to understand:

> Team cognition is critical to effective teamwork and team performance [22]. The current working definition of team cognition encompasses the organized structures that support team members' ability to acquire, distribute, store, and retrieve critical knowledge [5]. An ability to share crucial information, and know where in the team unique knowledge resides, allows members to anticipate and execute actions as a unit rather than as individuals. [34]

> Cognition is conceptually distinct from both behavioral process and motivational states. Behavioral process describes synchronization of joint actions, information sharing, and backup behavior—all of which impact team performance by aligning

> the unique contributions of team members [79, 100]. Motivational states describe emotional attraction to the team, beliefs about its capability to perform tasks, and the like. On the other hand, cognition describes the knowledge architecture of the team. [22]

In short, it is how teams gather, store, and use information. The emergent processes that handle information are often observable in communication between team members. Such processes include, for example, determining where, when and how to distribute information; how to collect that information in the first place; deciding which information to attend to at any given moment; directing that attention; and coordinating activity around specific information. In high performing teams those processes are often highly structured. In elite LoL teams, which player is in charge of a given piece of information, which mode of communication (e.g. voice, text, or pings) that player uses to store that information, and when that player distributes that information are all predetermined by a cooperatively constructed set of rules [96]. The result of knowing and following those rules is an emergent architecture of knowledge acquisition, distribution, storage, and retrieval [34] that allows the team as a whole to make sense of and make use of far more information than the players ever could as individuals.

Team cognition, and especially Cooke, Gorman, Myers, and Duran's [18] Interactive Team Cognition, deals exclusively with the team level of analysis. In this approach, cognition is defined as an activity:

> Physical properties of cognitive systems may include brains (neurons and glial cells), sensory apparatuses (receptor cells; neural pathways), and functional properties, including memory, perception, etc. Although certain properties are understood to be properties of cognitive systems, those properties alone do not constitute cognition. We argue that cognition is an activity that is realized when

> the physical system (e.g. a nervous system) comes into active contact with the information in its environment, such that the cognitive system exhibits functional properties. Simply put, cognition is not a thing or a place in the body or the environment; it is an interaction between the two. This is not to deny the inner phenomena associated with cognition, such as memories and dreams. Just as cognitive artifacts linger in the environment (e.g. tools, language, books) so can cognitive artifacts linger in the body (e.g. memories). Nevertheless, these artifacts are retrospective and devoid of meaning without some original reference to their source: the dynamic intersection of body and environment. [18] (p. 266-267)

One implication of this view is that team cognitive processes are directly observable in the interactions between team members working on cognitive tasks. Analyzing cognition on the team level, then, does not require assumptions about the contents or inner workings of individuals' minds. It deals in observing collective processes, including team attention, transactive memory, shared mental models, and macrocognitive collective problem-solving. Team attention will be discussed in a later section. Transactive memory systems, shared mental models, and macrocognition are discussed in this section as examples of some of the processes that comprise team cognition. Each of them are developed through team interactions, and each can be observed in team communication.

2.1.1 Transactive memory systems

Socially situated team cognitive processes for information storage and retrieval may also be referred to as a transactive memory system [85]. A transactive memory system, first proposed by Wegner [123], develops when members of a group have "a shared awareness of who knows what" (p. 60) [85] to ensure the group as a whole does not lose important knowledge even though no individual member can remember all of the available information. Moreland, Argote, & Krishnan's [85] experimental findings bolster the claim that there are emergent group features that cannot be accounted for by simply combining the individual cognitive resources of group members. In an experiment, they divided participants into groups of three to assemble an AM radio together. In one condition the three group members trained together before attempting to assemble the radio, while in the other, the group members trained separately and only came together when it was time to begin the trial. Importantly, the training sessions for all participants were identical save for whether they were alone or with their group mates. The researchers' hypothesis was that training together, and in the process developing a transactive memory system, would lead to better recall of the correct procedure and fewer errors in assembling the radio. Indeed those were their findings.

In a second experiment, the researchers attempted to replicate those results with a similar procedure and the addition two new conditions to allow evaluation of alternative explanations for those in the group training condition to outperform their counterparts in the individual training condition. These alternatives included group formation, since newly formed groups tend to perform worse than well-established groups, and strategic learning of how to overcome coordination problems, since training together could encourage group members to learn strategies that improve performance in groups regardless of knowing who possesses what information. The first new condition matched the individual training condition with an added team-building exercise. The second new condition matched the group training condition except the group assignments changed between the training session and the trial session, so that everyone in this condition trained in groups but none of them trained with members of their trial session group. Participants in the former condition had an opportunity to begin group formation but did not get to develop a transactive memory system, while participants in the latter condition had an opportunity to learn strategies to overcome coordination problems in groups and even had an opportunity to develop a transactive memory system, but that system was made irrelevant by the scrambling of groups for the trial session. The only statistically significant difference in group performance between conditions in this experiment was that the groups that trained together and stayed together for the trial recalled more of the procedure and made fewer errors assembling their radios than groups in any of the other three conditions. These results strongly support the claim that having a transactive memory system mediates group performance.

Transactive memory explains a portion of group performance that is not measurable on the individual level of analysis. Establishing where specific information resides in a group and how to access it, though, requires only some of the group processes that comprise team cognition. The fact that transactive memory predicts group performance supports the idea that we can use the study of team cognition more generally to understand team behavior and performance, but also begs further examination of whether other aspects of team cognition have been found to explain portions of group performance.

2.1.2 Shared mental models

The concept of shared mental models (SMM) describes another portion of the facets that make up team cognition. Where transactive memory is the system of knowledge allocation and retrieval, SMMs are the understandings and representations shared across teammates [82]. On a LoL team, for example, which player is responsible for knowing that the enemy mid laner's ultimate ability is unavailable for 60 more seconds is described by the transactive memory system, while the understanding that the enemy mid laner not having their ultimate ability means the team can more safely engage in a fight is part of a SMM.

To examine hypotheses about whether the presence of SMMs relates to team performance, Mathieu, Rapp, Maynard, and Mangos [82] interviewed and surveyed U.S. Navy air traffic controllers. They developed measures of task-related SMMs and team-related SMMs based on the interviews. Those instruments were used to measure consistency between team members' opinions about different approaches they might use in air traffic control (ATC) scenarios (task SMM) and about how one team member's actions would influence the rest of the ATC team (team SMM). The task SMM instrument presented participants with challenging scenarios and asked them to rate four potential courses of action based on how likely were to take each in response to the scenario. The team SMM instrument presented participants with courses of action taken by a coworker and asked them to rate each based on how positively or negatively they would impact other parts of their ATC team. Measurement of team effectiveness employed an instrument that asked participants for ratings of team technical expertise, teamwork, and team information exchange through a series of items each. In order to measure SMMs and not individually preferred courses of action, the focus of analysis for the SMM instruments is the consistency of ratings across a team, as opposed to how any one participant rated each item. While the researchers did not find a statistically significant relationship between team SMMs and team effectiveness, they did find significant correlation between task SMMs and team effectiveness. In their discussion, the researchers question whether their team SMM measure contained entirely valid items, given how consistently effective teams rated items on the task SMM instrument and how inconsistently they did so on the team SMM instrument. As reported, these results do still provide convincing evidence for the importance of shared task-related mental models to team performance in the domain of air traffic control, supporting the study of team cognition more generally as a framework to better understand team performance.

2.1.3 Macrocognition and collaborative problem-solving

While transactive memory systems and shared mental models tend to be studied in circumstances the teams being analyzed are generally familiar with, Fiore et al. [36] define the construct of macrocognition to address "the process of transforming internalized knowledge into externalized team knowledge," especially in less familiar environments [36]. Jentsch, Burke, Salas, Rosen, and Fiore [35] in their chapter on macrocognitive complex team problem-solving processes explicitly lay out subprocesses of this kind of team knowledge-building, including (a) uncertainty reduction about information, which requires pattern recognition and mental models; (b) uncertainty reduction about teammates, which requires sharing unique knowledge, recognition of expertise, and knowledge interoperability ("We conceptually define knowledge interoperability as the result of team members learning to represent the gathered information as knowledge objects, icons, or boundary objects" (p. 150)); (c) shared problem conceptualization, which requires visualization of data, knowledge sharing and transfer, developing common ground, and developing a team problem model; (d) consensus development, which requires option generation, intuitive decision-making, critical thinking, mental simulation, negotiation of solution alternatives, and storyboarding; and (e) outcome appraisal, which requires feedback interpretation and potentially replanning. Finally, Wiltshire, Butner, and Fiore [128] present findings from a study of phases in macrocognitive collaborative problem-solving (CPS). The goal of the study was to identify transitions between "distinct qualitative phases exhibited during effective problem-solving" [128]. To do so the researchers recorded the communications of 40 dyads working on NASA's Moonbase Alpha computer simulation, in which a meteor damages a moonbase and the dyad "must collaboratively solve the problem of repairing and restoring critical components of the system using a variety of tools to restore oxygen" [128]. These communications were coded by CPS processes like those detailed by Jentsch, Burke, Salas, Rosen, and Fiore [35]. Analysis involved making a time series of those coded transcripts and calculating entropy along each time series. Greater entropy in this context means more variability in the sequence of codes in that time period. Peaks in entropy between low entropy periods, then, are interpreted to be transitions between phases of collaborative problem-solving.

> To better understand the meaning of this calculation, consider the following example. Assume that there is a communication series where there are only two

> possibilities: knowledge request and knowledge provision. If there were a case where the probability was 1 for a single communication code (e.g. knowledge request), then there would be a probability of 0 for all other codes. If we were to plug these values into the equation we would get a very low or 0 value. There is no variability in the sequence of values and it is, therefore, highly ordered. Recall that higher entropy is associated with more disorder and lower entropy coincides with more order. Now consider a case where there is an equal probability of observing any one of the communication codes. The entropy value would be maximized, representing very high disorder, and perhaps randomness, because we can say with very little certainty that one state or another will be exhibited. [128] (p. 142)

In other words, each phase (e.g. "knowledge construction, team problem model, team consensus, and evaluation revision" [128]) in CPS during the task is characterized by an orderly distribution of certain processes (i.e. little variability of codes, and therefore relatively low entropy) and the transitions between phases are characterized by disorder as the team shifts to a new set of processes that vary greatly from the processes of the previous phase (i.e. lots of variability of codes, and therefore relatively high entropy).

Indeed every single team showed robust peaks indicating separate phases of CPS. Furthermore, every single code varied significantly across epoch time, leading the researchers to infer that there is consistency in when (i.e. during which phase) each process is employed. In addition to identifying CPS phases, Wiltshire, Butner, and Fiore [128] assessed performance in terms of how long it took the dyad to restore life support, how much oxygen the dyad was able to restore, and how many objects the dyad was able to repair. Average peak entropy significantly correlated with worse performance in these three areas. In other words, the more order a dyad was able to maintain in which processes they employed when transitioning between CPS phases, the better they performed in Moonbase Alpha. Again an aspect of team cognition, specifically complex collaborative problem-solving, has been found to help explain team performance.

Transactive memory systems, shared mental models, and macrocognition each describe a part of team cognition, and the presence of each in a team has explanatory power when it comes to team performance. The fact that they are all inherent parts of any team that acts as a single cognitive unit distinguishes them from the practices explored in the next subsection. In fact, for a team that does not act as a single cognitive unit – that does not possess these aspects of team cognition – the following practices would likely do little for performance. The hypothesis arises, then, that team cognition has an influence on the relationship between the following practices and team performance, as illustrated in figure 2.1.

2.2 Team Performance across Domains

A number of practices have been found to correlate with team performance across multiple domains. These practices include consistent and structured communication, purposeful role differentiation, spatial and temporal coordination, status distinctions between team members, and strategies for managing stressful situations. Note that these are not the characteristics that define the kind of isomorphic teams under analysis. Those defining characteristics deal with the structures and processes inherent to teams in this category. These practices that predict team performance are behaviors that teams can enact but that are not inherent to their work.

Figure 2.1 illustrates how team behavior is comprised of both domain-specific practices and more general practices that apply to teamwork in isomorphic teams across domains. This section explores each of the more general practices that have been found to predict

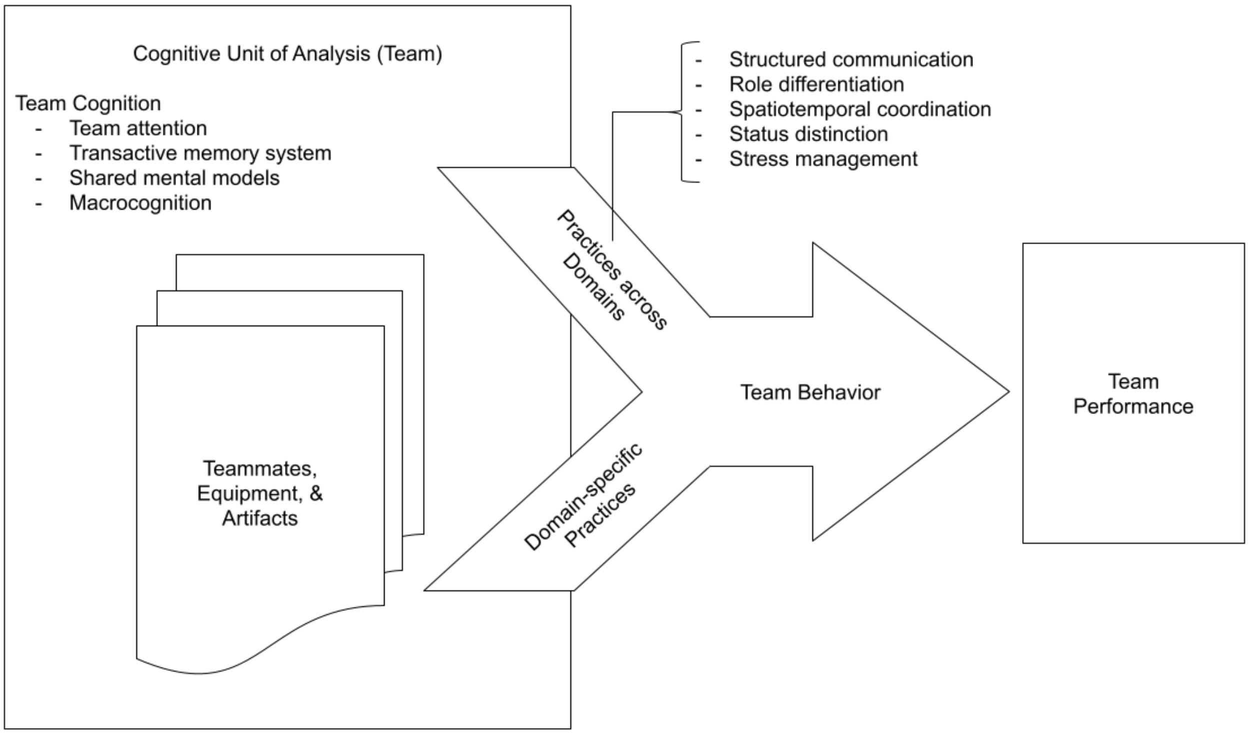

Figure 2.1: Team cognition connects to team performance through its manifestation in team behavior. Aspects of team cognition are observable in and influence the effectiveness of collective behaviors, as indicated by the overlap between the cognitive unit of analysis box and the behavior arrow.

performance and offers examples of how they can influence performance in esports. Note that these behaviors originate on the team level of analysis. This characteristic of figure 2.1 is intended to emphasize that, while there are certainly individual practices that comprise team behavior, each team member is on the same level of analysis as the tools in their task environment. In other words, the team, comprised of people, technology, and artifacts produced during a task, is the cognitive unit in this approach. The interactions between team members, other team members, and information in the team's environment are what comprise team cognition, as opposed to simply the sum of the cognitive processes in the individual team members' heads. The behaviors enacted by the team as a result of these team cognitive processes then result in the team's performance on a given task.

2.2.1 Team Communication

Better understanding how teams communicate under stress could have implications for team training and safety beyond the world of competitive video games. Looking at how communication relates to performance is not new. Researchers have highlighted how particular communication practices, like checklists, make aircraft navigation [61] and patient care safer [13]. Catchpole et al. even translated Formula 1 pit crew communication structures to improve information transfer between surgery and ICU teams during patient handoff [13]. In doing so, they reduced technical errors and information handover omissions, all while shortening the duration of handovers. Teams in disparate domains, then, can benefit from similar communication practices under similar pressures.

N. Taylor's [113] ethnographic study of a competitive Halo 3 [10] team found that competitive players value consistent communication as a factor of successful performance. He describes an interaction in which one player, named Shadow, is giving another feedback after a game, and both players tacitly reinforce the importance of in-game communication, despite the fact that they disagree about the quality of communication in the game that just ended:

> After the match, Shadow criticizes one of the team's members for not being loud enough. "When you do badly don't be quiet – you weren't talking!" he says, leaning in after some seconds trying to get the other player's attention. When the other player defends himself, claiming "I was yelling," Shadow replies that the only player he heard making callouts was "OldSchool," another player on the team. This interaction suggests a shared conception about the importance of "being loud" to successful play: Shadow's critique, and the other player's defense, suggests that the team lost in part because one player wasn't audible enough in his callouts. [113] (p. 262)

Neither player in that interaction, however, emphasizes the need for discipline and structure in in-game communication. Given the emphasis on structured communication in esports and teams research, one potential explanation for its absence in this interaction is that the players value any communication over no communication, leaving room for refinement for when they have everyone actively contributing. In fact, professional PlayerUnknown's Battlegrounds [20] player Kaymind, when asked about how his team handles situations where communications get too chaotic, responded, "When one of us feel we realize, 'Alright, it's getting too messy.' You just say 'Reset!' " [126]. Kaymind's teammate, Nerf, elaborated that hearing reset "makes everyone stop thinking about what they're [individually] doing and then just refocus and come together" [126]. Nerf and Kaymind's team is known for sending one or two members across the map as scouts, and they stand by this strategy. Nerf is not, then, talking about coming together spatially. The refocusing he describes is a communication- and attention-based process in which the shotcaller either gives a command to coordinate the team's activity or starts a discussion to collect all of the information the team currently has about enemy positions and their options for future positioning. This predetermined cue demands a return to structure and joint attention from a state of disordered, individual focus. It gives the team the ability to recentralize executive control of attention when it grows too scattered and overloads each individual player's ability to attend to relevant information and make decisions.

Gorman et al. [45] studied those effects between the behavioral level of analysis and the neural level of analysis in teams of U.S. Navy Submarine School students undergoing submarine piloting and navigation training. The researchers found that in more experienced teams, changes in communication patterns occur before changes in the neural patterns (i.e. changes in patterns of electroencephalography readings) of team members. These findings are in line with Nerf and Kaymind's description of their process of resetting: first the style of communication changes, then the team comes together. To find these results, Gorman et al. [45], collected two kinds of data – EEG readings and communications – over three phases of training – brief, scenario, and debrief. From the EEG readings, the researchers established individual engagement over time [1], which were in turn aggregated into a discrete team-level state, called the neurophysiological symbol (NS), once per second. Calculating the entropy of NS over time, Gorman et al. [45] found this measure of changes in neurophysiology at the team level to correlate with changes in training phase and that mean NS entropy predicts team experience level. To analyze communications, the researchers used latent semantic analysis (LSA), a means of analyzing linguistic content for how strongly it relates to a particular domain of knowledge. They found that communication patterns also covaried with training phase and predicts team experience. To test for cross-level effects between neurophysiology and communication patterns in these data, they used lagged cross-correlation functions which found that "increases in the amount of domain-specific content of utterances (large vector lengths) tend to precede a more flexible neurophysiological distribution (high entropy)" (p. 191) in more experienced teams, while neither changes in neurophysiology nor in communication consistently precede the other for less experienced teams. In other words, for experienced teams, neurophysiological state tends to change before communication patterns, but for inexperienced teams neurophysiology and communication patterns are only related to each other at each timestamp. In short, the major contribution of this work is in finding cross-level relationships between the neurophysiological level and the semantic level in teams.

This understanding that we can observe cross-level effects, and furthermore that cross-level effects can predict team experience level provides a more complete view of team performance than if we took team performance only to be the result of individuals' cognitive processes. Joint action research provides us with the individual cognitive "mechanisms that appear to be crucial for the successful coordination of action" [103], such as representation sharing, action prediction, and joint attention. It is focused on understanding the cognitive abilities required of individuals to successfully coordinate with others. This work focuses on the team

[1]Using software trained on a separate dataset.

level of analysis, so while those mechanisms are clearly crucial for high performance teams, the practices highlighted in this section are not performed by individual members in service of coordination. Rather, they are performed by the team as a whole. Moreland, Argote, and Krishnan [85] explain this difference clearly in the introduction to their chapter on socially shared cognition and group performance:

> There are two general ways in which such cognitive processes could be studied [62]. Most researchers focus on cognition about groups, studying such phenomena as self-categorization [7], outgroup homogeneity effects [65], the group attribution error [1], and so on. Their work explores how individuals process information about groups and their members (including themselves). A few researchers, however, focus on more complex phenomena involving cognition by groups. Their work explores how groups process information for their members. Information processing by groups requires socially shared cognition, that is, collaboration among members who seek to encode, interpret, and recall information together rather than apart. (p. 57)

The fact that these group effects can be observed between distinct levels of analysis – semantic patterns and neural patterns – supports the use of communication as an operationalization of team cognition [18]. In this sense, Kaymind's "reset" cue is part of a cognitive process to manage attention on the team level when individual members can no longer maintain it.

2.2.2 Roles, status, and team structure

In Reeves, Brown, and Laurier's [95] description of expert Counter-Strike [121] play, they describe a scenario in which teammates form a line to move down and clear a hallway. A player's position in this line, they explain, dictates what they are expected to do if they spot an enemy. A player in front, having the clearest line of sight and being the most exposed, is to shoot first, while a player in back, covered by teammates, is to keep tabs on their positions, keep distance, and choose shots carefully to avoid shooting teammates in the back [95]. The role of each player on the team is therefore determined by the situation in that moment, and that role determines what a player attends to so that the team as a whole can attend to as much task-relevant information as possible. After all, if a player in front is trying to keep track of the positions of the teammates behind, and a player in back is trying to be the first to spot an enemy down the hall, it is much more likely that the player in front, who is both more exposed and better positioned to do damage, will be late to react to an enemy, and the player in back, who has teammates in their way, will hit a teammate when they aim for the enemy.

Situational roles, then, are determined by the task, but less transient roles – bestowed on team members because of abilities, status, or organizational goals and processes – can influence performance just as easily. Whether a team member has high or low status in the group can determine the amount and content of communication they receive. Status can also influence how well their ideas are received by other team members [27]. In their review of research on teamwork in extreme environments, Driskell, Salas, and Driskell [27] make it clear that the process of determining status differs from the coerciveness of power. The allocation of status is a cooperation between group members, and the effects of status differentiation between teammates can increase cooperative practices in stressful circumstances. As a task grows in difficulty those with high status become more accepting of input from lower status teammates, and those with low status rely more heavily on their high status teammates' decision-making [27]. In other words, in teams with status differentiations, members look for feedback and direction from their team as tasks get more difficult. This phenomenon can be key to success, because it is likely that the knowledge needed to succeed distributed unevenly across the team. Differences in status can encourage members to rely on their teams transactive memory system and knowledge-building processes to solve problems together, rather than separating from the team's conversations and trying to perform a task with only the information available to one teammate.

While status can create an implicit hierarchy, explicitly defined roles and team structure are common characteristics for teams that work in high pressure environments. According to Salas, Rosen, and King's [101] principles for effective teamwork in emergency medicine, one of the benefits of well-defined roles and structure is that each part of the team gains a better understanding of the tasks and abilities of their teammates. Even without having performed their teammates jobs in the past, knowing other members general tasks "allows team members to formulate accurate expectations of their teammates' actions and needs during high-stress work episodes" [101]. This hypothesis is supported by research on how turnover affects group learning and performance. Devadas and Argote [23] (via [85]), for example, found that clearly defining roles reduced the well-established penalty to overall productivity after new members join a team. It is particularly noteworthy that strengthening team structure seems to be more effective at mitigating the negative impact of turnover than task-relevant training for the new members [2] (via [85]). These researchers conducted an experiment in which they assigned groups to make origami swans. One condition experienced no turnover, a second condition experienced some turnover, and a third condition experienced some turnover but the newcomers were trained in folding swans before entering the group. There was no significant difference in the detriment to productivity experienced by the two conditions that had turnover, even with training for one condition's newcomers and without for the other's. In Salas, Rosen, and King's [101] words, having clearly defined roles and structure "allows team members to formulate accurate expectations of their teammates' actions," because they share understanding of their teammate's goals and context.

Popular esports can differ from each other in how higher level roles are assigned. In some, roles are designed into the game. A LoL team, for example, has five distinct roles – top laner, jungler, middle laner, support, and bottom laner – each of which has different strengths and responsibilities, regardless of the level of competition of any given game. Counter-Strike: Global Offensive [121], on the other hand, has no such structure coded into the game, and competitive teams have instead developed common roles – entry fragger, second man in, AWPer, lurker, and support, to name a few – to organize plays and develop strategies around. The fact that the most competitive teams universally have well-defined roles for each player, even in games where no such structure is part of the game design, supports the argument for roles and team structure having an influence on performance.

2.2.3 Spatial and temporal coordination

For teams that work synchronously under temporal pressure, coordination in time and space has an established correlation with performance. The best evidence for this in competitive video games is the work of Drachen et al. [26] analyzing the movement of Dota 2 [21] teams of varying skill levels. Drachen et al. [26] collected position data for every player in a game for 196 games across four skill tiers. They then analyzed those data in terms of how often team members moved from one zone on the map to another and how far apart teammates were from each other over the course of the game. They found that better teams kept teammates closer together and had teammates swap positions on the map more frequently over the course of a game.

While these operationalizations of spatial and temporal coordination may be unique to Dota 2, the relationship between the constructs of coordination and performance is not. In addition to the obvious examples of sports teams like Formula 1 pit crews, for whom tightly coordinated action is the explicit goal [13], evidence from cockpits [107] and operating rooms [101], make it clear that many errors occur when team members' activity is not linked in time and space. Kane and Luz [66], for example, analyzed how multidisciplinary medical teams meet and operate as a system. Through a combination of observations of team meetings, semi-structured interviews with permanent team members, and questionnaires at the beginning of the study and after one year Kane and Luz [66] report that without the coordinated completion of tasks in a timely manner, “the system will fail” (p. 525). They note three issues of temporal coordination that are crucial to the team’s work: “the synchronization of work routines, extra time needed for case discussion in teleconference and time to coordinate materials” (p. 526). When the rhythm of the team meetings and team’s work is not synchronized with that of individual members, the entire system takes more time than its members can afford to spend not working on specific tasks (Kane Luz, 2006). From their study of a redesigned hospital emergency department, Valentine and Edmondson [120] illustrate scaffolding of effective coordination for transient teams and explain how it can improve team performance. This study utilized both qualitative interviews and a quantitative performance impact analysis of the pods system that came with the redesign. Importantly, the scaffolds highlighted include clear boundedness to who belongs on the team, a clear set of roles for the team, and collective responsibility of everyone on the team for the results of their collective work. Except for collective responsibility, which for more permanent teams is often assumed, these attributes reflect practices this section has already discussed as relating to team performance across domains. Boundedness and role sets are both vital to the team structures described previously, and their positive influence on group coordination described by Valentine and Edmondson [120] point to mediating relationships that may exist between the practices discussed in this paper. The quantitative data from this study centers on the performance impact of the implementation of pods – physical locations that force spatial and temporal coordination. Indeed, pod use was significantly correlated with speedier work without an increase of errors in patient care.

While further research narrowing in on transfer is obviously needed, these reports of higher performance correlating with spatial and temporal coordination in both competitive video games and emergency medicine reinforce a central argument of this work: lessons learned in the pursuit of improved performance in teams could help in seemingly disparate domains, if the teams within those domains share certain characteristics. Examples of specific characteristics are discussed in detail in chapter 5.

2.2.4 A note on stress and team cognition

The most important times to perform well are often also the most stressful. Stress can impact team performance by narrowing attention onto individuals and away from team processes [27]. Driskell, Salas, and Driskell [27] note that teams under stress tend to communicate less as a result of their narrower focus. Less communication means that team cognitive processes and states that emerge through communication and interaction between teammates lose their structure and frequency. Without that interaction, a team is no longer working on cognitive tasks as a unit. Instead, each member tries to solve problems on their own and coordination and strategy fall to the wayside. These situations illustrate why cohesion and structure can be so closely tied to performance. A cohesive team will maintain a team perspective more easily. A team with a well-defined structure and understanding of each member's role will continue to solve problems as a single cognitive body instead of splitting into individuals separately trying to solve the same problem using only their individual attentional resources. This is especially true if a dynamic situation calls for team members to swap roles or otherwise deviate from their usual structure. Team cognition is not a property or a strategy, so it is incongruous to talk about how having more or less team cognition relates to performance. Instead, the logical claim is that teams whose members more frequently interact with each other and the available information – in other words teams that display team-level cognitive processing – are more likely to perform well under stress [27].

2.3 Team Taxonomies

Teams research has produced a number of team taxonomies, like those described by Wildman et al. [127], which detail characteristics and task types to establish categories of teams that transcend the fields in which they work. In parallel with those theoretical efforts, intervention studies and experimental designs have successfully translated findings across domains, like Catchpole et al.'s [13] work decreasing errors during patient handover between Operating Room and Intensive Care Unit teams using data from Formula 1 pit crews and aircraft navigation. It is rare, however, for studies that attempt to generalize team practices across domains to discuss their findings in terms of taxonomic theory.

In 1973, Newell called on cognitive science and artificial intelligence research

> to focus a series of experimental and theoretical studies around a single complex task, the aim being to demonstrate that one has a sufficient theory of a genuine slab of human behavior. All of the studies would be designed to fit together and add up to a total picture in detail. [88]

In 2017, Gray asserted that "games represent the type of experimental paradigm that Newell was advocating and ... provide the technologies and data needed to realize his vision" [48]. Taken together, the theoretical and methodological suggestions I rely on in this work agree that elite esports play is such a setting.

While the study reported in chapter 4 focuses on communication under pressure in *League of Legends* (LoL) teams, esports teams from different games can display distinct characteristics. In other words, while LoL teams may belong to a certain category of team described in chapter 5, teams from other esports may share characteristics with other kinds of teams. Delineating the team characteristics necessitated by different genres of esports, inducing a taxonomy that encompasses the variety of these characteristics, and testing findings across domains according to that taxonomy will both expand our methodological tool set for studying high performance teams and refine our theoretical understanding of generalization across domains.

2.4 Esports

Esports' growth creates opportunities for studying people and systems on a massive scale. Research around esports, however, is still in its nascency. In a review of esports research [97], my colleagues and I identified the disciplines and research trends prominent in the literature so far. These findings provide context for my call for more rigorous, generalizable work using esports as a research environment and experimental paradigm.

2.4.1 Disciplines Studying Esports

Each discipline publishing work around esports is included in this section to give a complete background of esports research. Cognitive Science, Informatics, and Sociology are presented first for their relevance to the present study.

Cognitive science

Research in cognitive science and psychology has focused on player performance and cognitive and behavioral differences between novices and experts. Until recently, this work had relied on naturalistic observations to better understand the cognitive processes required for competitive play. The earliest research explored how competitive players understand the games they play and the contexts they play them in [3, 94], and through these explorations, a trend developed of studying what sets the elite players apart. Huang, Yan, Cheung, Nagappan, and Zimmermann [59], for example, collected data on habit formation in StarCraft II [30] players. Expert StarCraft II (SC2) players, according to Huang et al. [59], develop habits in consistent ways, yet those habits can be unique to individual players. In other words, the same methods for developing good in-game habits at a high skill level are used by many players, but which habits they develop differ by player.

Experimental work on cognition in esports is less common but growing, as noted in W. D. Gray's [49] call for action games to be "an experimental paradigm for Cognitive Science" as a context in which to explain complex human behavior. P. B. Gray, Vuong, Zava, and McHale's [47] experiment studying hormone levels during *League of Legends* [42] play exemplifies the foundation building required for competitive video games to become a central experimental paradigm for cognitive science. In the 26 subjects who played against human players, P. B. Gray et al. (2018) found no significant difference in testosterone, cortisol, dehydroepiandrosterone (DHEA), androstenedione, or aldosterone levels when compared to the control group of 17 subjects who played against the computer. In both groups, aldosterone levels decreased during play, and as games against other people lengthened, testosterone, DHEA, and androstenedione levels increased. In short, these are null results. The authors, however, identify the consistent cortisol and decreasing aldosterone levels as indicators that the context of their study — "an informal, familiar location playing against known competitors" [47] — facilitated less competitive, more relaxed play. Gray and colleagues suggest future work uses a more competitive venue, highlighting the nascency of esports research.

Informatics

Esports research in informatics collects from a wide variety of data sources including game telemetry and user-generated play data [29], physiological data [86], and text mining [90] in combination with observations to analyze in-game performance, team dynamics and formation, and interactions between players. Esports' technology-mediated nature gives researchers this ability to collect massive amounts of data at various levels of analysis. For example, Low-Kam, Raissi, Kaytoue, and Pei [76] collected player inputs from replays of 90,678 professional SC2 matches and developed a machine learning algorithm to detect unexpected strategies in those data in the interest of informing models of player behavior. Work that focuses on team performance tends to rely more heavily on mixed-methods approaches. S. J. Kim, Keegan, Park, and Oh [68] demonstrate work that is representative of the team expertise research generally. They collected LoL game data from the Riot application programming interface (API) to access performance metrics, like kills, deaths, assists, wins, losses, and rankings, in addition to which champions each team selected in which order. The researchers also conducted interviews and focus groups with participants to provide context for their quantitative findings. Both the gameplay data and the participants' responses supported the hypotheses that (1) team performance is correlated with how familiar team members are with their assigned role, (2) team performance is correlated with the extent to which team members' roles complement each other, and (3) individual performance is correlated with a player's likelihood of selecting a role that compliments their team over a role that they are more proficient with.

Some informatics work around team dynamics in esports focuses solely on social interactions between players, largely ignoring in-game performance. Freeman and Wohn [40] developed an interview study to understand how esports players give and receive social support among themselves. The study of team performance, approached from these varied perspectives, exemplifies of informatics' multidisciplinary nature.

Sociology

Much of the work in the sociology of esports has explored questions around live esports events and the interactions between audience and gameplay [44, 118]. T. L. Taylor and Witkowski [118] demonstrate the kind of generative exploration possible in a live esports context. In their own words, live events "give us an opportunity to explore the ways games can be both contained within larger cultural activities and yet can also cycle back and shape how people think about their leisure time and identity more generally." In this vein of viewing games and esports as both a vehicle for and result of cultural change, they highlighted the growing numbers of women in competitive gaming spaces. Sociologists have focused more on gender and identity than on any other single esports research topic for its salience and social relevance to the esports community. The first of these papers on gender explored the presence of women in competitive video games [9, 115], but the field has recently adopted a focus on the perceptions of gender discourse in esports communities, as shown by J. Kim's (2017) [69] discussion of LoL players' perceptions of differences between genders in video game competition and of solutions for narrowing the gender gap in esports.

Articles in this line of inquiry have approached gender by juxtaposing the roles of women and the portrayal of masculinity in esports. For instance, researchers have asked about "invisible women" in competitive gaming [9], what roles women tend to take on in esports communities [115], and attitudes of professional players toward women, gender identity, and hypermasculine culture [99, 115, 116, 130, 133]. Although these questions lead researchers to conclude that gender inequality is currently a facet of esports [69], they also see esports as an opportunity to encourage a culture of diversity [115].

Business

The business literature dates the birth of esports back to the rise of the competitive scene of early 1980's arcades (Borowy Jin, 2013). Its growth is attributed to the value of the experience economy for consumers, the popularity of video games, the social recognition of video game players, and advances in technology [6] [105]. The identification of these factors has helped in exploring motivations for esports consumption, understanding the networks and organizations surrounding the players, and designing effective marketing techniques

[53, 73, 106, 124]. This research is most often done in a naturalistic setting using surveys, interviews, and case studies. For example, Hamari and Sjöblom [53] apply the Motivation Scale for Sports Consumption (MSSC) to measure motivation for esports consumption. MSSC has been used to measure motivation for traditional media and sports generally, so their results in a new context can be compared to previous work in more widely studied areas [53]. Esports has evolved into a complex ecosystem of consumers, players, organizations, and other stakeholders, where players and consumers are the most common subjects of study for business researchers. Seo and Jung [106] conceptualize esports consumption as an "assemblage of consumption practices, where consumers actualise and sustain the eSports phenomenon through their engagement with the interconnected nexuses of playing, watching and governing of eSports" (p. 637).

The convergence of Western and Asian esports cultures [105] has led to a focus on the internationality of esports. Parshakov and Zavertiaeva [92], for example, examine the relationship between a country's tradition of playing esports, its country-level characteristics (e.g. Hofstede's cultural dimensions), and the performance of players from that country by using tournament prize data. Other studies, however, have narrowed their research by analyzing both players and consumers in specific countries. The literature has expanded over the years from China being the only region analyzed [112, 132] to including research about communities in regions like South America [84] and Europe [75, 108].

Sports science

A group of sports science researchers interested in the implications of competitive video gaming are categorizing esports within the frame of traditional sports. Most publications from sports science are agenda setting—by using the standard of traditional sports, they are evaluating the potential of esports to be considered sports. Early discussion around cybersport [56] defined characteristics by which competitive computer games can be considered sports, namely how the immersion and interactivity of computer games can emulate and require skilled physicality. As work reconciling esports with traditional sports continued, Jonasson and Thiborg [64] inserted esports in Guttmann's [50] model of modern sports. This discussion continues in sports science, as illustrated by Hallmann and Giel's [52] summary of previous work providing the following criteria for esports to be categorized as sports: physical activity, recreation, competitive elements, organizational structure, and social acceptance of esports.

Empirical studies of esports in sports science are mostly case studies utilizing qualitative methods. Rambusch, Jakobsson, and Pargman [94], for example, conducted interviews with players at World Cyber Games (WCG) and discussed important elements shaping and influencing gameplay in Counter-Strike [121] on four analytical levels: (1) player actions during play, (2) interactions within and between teams, (3) players and fans on the Internet, and (4) the Counter-Strike gaming scene. These empirical studies tend to focus more on how players engage in esports competitions and less on whether participation in esports can be considered sporting.

Law

Law in esports is rooted in concern for how concepts of copyright and intellectual property are applied to virtual worlds. Law papers are primarily analyses of how a certain moral concept or right is affected or applied in the esports space. By tracing existing cases and compiling tests, authors discuss how legal concepts may influence or shape the governance of esports. Writing on how the virtual–analog division in esports creates a new opportunity for shaping Internet law, Burk [11] asserted that "copyright is likely to be the lynchpin in any dispute." Other legal concepts such as the right to publicity or rights derived from necessary associations in the space, gambling law, or international accommodations for sports will all be relevant as well, but governance or legal thought associated with esports must address the ownership of the game and the debate of where creativity and ownership lie. These have manifested as cases debating who has the right to use player-created avatars, who owns mods to a game, who may broadcast tournaments of gameplay. Historically, ownership—and responsibility—of games and associated products have been granted to companies, with player contributions classified as adaptations or derivative works [11]. While this leaves companies with some control over player-generated content, for instance, it also makes them at least partially responsible for the gambling, doping, and cheating that go on around esports. For this reason, classification of esports as sport or computer game is a frequent point of discussion in esports law because sports enjoy special accommodations in federal and international laws. As Holden, Kaburakis, and Rodenberg [57] noted, the legitimacy convenience granted by classifying esports as sports would, similarly, come with oversight; there seems to be tacit agreement that esports is en route to classification and regulation similar to traditional sports, although formal litigation models have only been suggested, not established in any state at time of writing.

Media studies

Research in media studies has focused on relationships between esports, sports, and media; the definition and delimitation of esports; the methodologies used to study esports; and the practice of live streaming gameplay. Themes such as the roles of physical exertion, spectatorship, historical precedence, and interaction are analyzed in an effort to classify esports. In these analyses, comparisons are often drawn between esports and chess, poker, and other traditional sports (e.g. [58]). The existence of esports across digital and physical spaces is possible, according to Hutchins [60], because of media, communication, and information flow. T. L. Taylor [117] also points out that "esports has encoded in its very nature a deep rooting in both technology and media" (p. 210).

Media studies researchers examine the esports community through the phenomenon of live streaming in the interest of exploring how the community is formed and how it interacts with streamers (e.g. [12, 24, 54, 67]). Based primarily on qualitative data such as interviews, observations, and content analysis, these descriptive papers examine the experience of being in various roles in the esports ecosystem. Before 2012, research took place around events celebrated in physical spaces, like the WCG (e.g. [60]). For example, Cheung and Huang [15] created a taxonomy of spectators and described spectatorship not as simply watching the game but as actively engaging with the community. The spectators described here are watching either from a physical venue or on dedicated video-sharing channels. Since then, technological advances, specifically live streaming and platforms like Twitch, generated a new media phenomenon which has been the primary focus of research for the last several years [12, 67]. The merged space between the in-person and online worlds has become a focus of the field, as seen in T. L. Taylor's [117], Whalen's [125], and Burroughs and Rama's [12] works discussing the distinctions and lack thereof between what is virtual and what is real in the context of streaming.

2.4.2 Trends across Disciplines

Contested definitions

Across disciplines, esports have been defined as competitive gaming, computer-mediated sport, or interactive spectatorship [39], with varying degrees of emphasis on physicality, computer mediation, institutional infrastructure, and spectatorship. Defining esports is a nontrivial debate that underlies scholars' framing of their research.

Competitive gaming is a widely accepted description of esports. Regardless of whether esports are classified as sports, their status as video games rooted in principles of game design is not contested. Proponents of this definition of esports do not consider the broadcast popularity and level of institutional infrastructure surrounding a game title to be factors in classifying a game as an esport [58]. Competitions can be held between amateurs and professionals, in a garage between friends or in a stadium between world-class teams. For esports titles that afford team play, scholars often focus on the formation and practices of teams (e.g. [41]) and how technology mediates team communication and gaming. Zang, Wu, and Li [132], for example, define esports as “a sport of wisdom between people with hi-tech software and hardware as sports equipment...” More recently, Hamari and Sjoblom [53] describe esports as “a form of sports where the primary aspects of the sport are facilitated by electronic systems; the input of players and teams as well as the output of the eSports system are mediated by human- computer interfaces” (p. 213). In these definitions, communication within a team or between competing teams is possible or enhanced because of the mediating technology.

Other definitions trivialize the role of technology, instead focusing on similarities with traditional sports. For example, one of the most cited definitions of esports is Wagner’s [122]: Esport is “an area of sport activities in which people develop and train mental or physical abilities in the use of information and communication technologies.” While Wagner himself equated esports to competitive computer gaming, in “On the Scientific Relevance of eSports” his definition of sports is inclusive of competitive gaming. In categorizing esports as sport, the physical motion of traditional sports is given less weight than the cultural significance and formal support of the activity. Support for this view of sports is growing as governing bodies emerge to guide developments in esports spaces and as “the development of a nascent professional infrastructure [includes] features familiar from the world of physical sports of entertainment, including tournaments, leagues, fans, teams, team owners, player contracts, sponsors, and the like” [117] (via [11]). Similarly, systems of prize and payment within a “professionalized context” [117] (via [8]) perpetuate the parallels between traditional sports and esports. These similarities make sports terminology useful for both players and researchers in talking about practices and issues in esports.

Comparisons to traditional sports are also a useful measure of the scope of spectatorship. This perspective on esports emphasizes the union of media and competitive gaming by focusing on the community and technology of spectatorship that surrounds esports ([67]). The most precise definition is given by N. Taylor [114]:

> E-sports involves the enactment of video games as spectator-driven sport, carried out through promotional activities; broadcasting infrastructures; the socioeconomic organization of teams, tournaments, and leagues; and the embodied performances of players themselves. [6, 55, 117, 114, 130]

Emergent platforms such as Twitch and YouTube have allowed streamers to serve not only as players but also as performers and entertainers. The levels of governance and organization that parallel that of sports is driven by a desire to establish the legitimacy of esports to the public, media, and investors because it is already "an important social and cultural instrument of the youth" [119]. This view highlights the cultural significance of socializing around play.

In short, esports are often defined as games, as sports, or as mass entertainment. These definitions are not mutually exclusive but stem from different frameworks for understanding esports. They also each have unique practical implications, like leading to the regulation of esports under the same laws that govern traditional sports.

Nature of expertise

Researchers in cognitive science, informatics, and sociology each study expertise in esports through different levels of analysis. Cognitive scientists are looking at the performance of individual players, who may or may not be nested in teams, and aim to identify constructs previously explored outside of esports that correlate with higher skill levels in competitive play. Huang and colleagues [59] summarized in the esports within the disciplines: Cognitive Science subsection exemplify this approach relying on practice, routine, and habit formation literature from contexts as disparate as construction work and chess to understand expert SC2 players' in-game behavior.

In informatics, more work has been published on expert teams than on individual performance. Informatics researchers often implement gameplay data analysis in search of optimal team compositions [46] and patterns in team play that correlate with in-game performance [72]. Pobiedina, Neidhardt, Moreno, Grad-Gyenge, and Werthner [93] and Nascimento, Melo, da Costa, and Marinho [87], for example, both use the team-level data available from game publishers' APIs to test hypotheses about what makes a strong team. They identify factors like role distribution, role selection, player experience, and teammate familiarity [93] and statistics like ward placements and neutral minion kills [87] as factors that correlate with how often a team wins.

Sociologists look at broader social structures to examine what goes into expertise beyond in-game performance. Witkowski [129], in her doctoral dissertation, includes a section on what it takes for players to make it to professional teams. While honing in-game mechanics is fundamental to professional play, she emphasizes the necessity for players to develop social, business, and tech savvy. From interviews and observations of these elite players, the author details the out-of-game work and knowledge necessary to be considered an expert:

> Players spoke of the self-promotional work outside of the game that aided in their upward mobility: Recording game footage and minimally overlaying it with tactical voiceovers then placed on YouTube, winning a duelling tournament organized by a prominent blogger, participating on Arena specific forums as a knowledgeable poster, making extravagantly produced gaming movies for Warcraftmovies.com (using a video editing program and adding music, effects, and

> text), or attaining a spot as a regular blogger on one of the major Arena community pages are just some examples of the extracurricular busy work that experts have engaged in during their rise to the top. [129] (p. 71)

While cognitive science focuses on what expertise is for a competitive player, informatics on what it is for a team, and sociology on what it means outside the game, these differing views of what constitutes expertise are not in conflict. To encompass what an expert is in an esports community, we must account for each of these perspectives.

The state of nascent research

For now, much of esports research is naturalistic observation of ecosystems without intervention. As the field develops, we expect more experimentation to add to this body of exploratory and descriptive work. Surveys are common, but for many, the representativeness of their samples is difficult to assess. They are often limited in their scope to specific regions, age groups, or games in an effort to produce knowledge useful in a business context.

An advantage of this wealth of exploratory knowledge is that it has already produced research questions for experimental designs. For instance, is the relationship Leavitt, Keegan, and Clark [72] found between ping usage and player performance in LoL causal? What about the correlation they found between pings and deaths? Designing experiments that might help reconcile findings that we can only make inferences about will produce much work of interest to both the esports community and researchers' respective disciplines.

The amount of work using API data also continues to grow. The wealth of data we can capture without intervention allows for naturalistic data collection on a scale that would not otherwise be possible. Reliance on these APIs, though, means that the metrics we use to predict performance, for example, must be narrowly defined and restricted by the data available from an API. Many APIs offer massive amounts of game data but do not supply a few key statistics, like player position. Researchers have thus far either restricted their models to data that are available through an API or created their own tools for gathering more data locally, restricting their sample size to the number of players they can bring into a lab. Game publishers' fears of releasing too much data are well founded. Many have had issues with cheaters using game data to create tools that give them an unfair advantage. Finding solutions for industry to enable researchers to access richer data sets, though, would permit much less restricted models of player and team performance.

Esports research's nascency means there are still fundamental questions about how the field is unfolding. It means researchers involved in the early work – and those introducing the space to unfamiliar fields – have an opportunity to shape its growth. We can examine the assumptions made, like how esports is defined, and how those assumptions support or exclude people, ideas, generalizability, and specificity depending on what that definition considers part of the world of esports. Fields and individual researchers cannot avoid having lines of inquiry that are only concerned with a specific aspect of the ecosystem. They can, however, contextualize that focused work to avoid making communities and practices invisible that are fundamental to the creation and continued existence of their specific interest.

Chapter 3

Communication & Expertise in *League of Legends*

To provide an overview of how communication and expertise are related in *League of Legends* (LoL), this section is adapted from the findings of a paper I published in 2018 titled, Distributed cognition and temporal knowledge in *League of Legends* [96]. This paper reports on a case study of a team of former and future professional players in their first year of working as a team. The LoL overview that begins this section includes explanations of game mechanics, player roles, and team strategies necessary for parsing the data and findings.

3.1 *League of Legends* Overview

League of Legends, a multiplayer online battle arena (MOBA) developed and published by Riot Games, pits two teams of five against each other in a contest to destroy their opponent's base, or nexus. The map (appendix A) is a square with one team's base in the lower left corner and the other's in the upper right. Between the two bases are three lanes called the bottom lane, mid lane, and top lane. Before play begins, the two teams enter a draft phase in which each team bans five characters, or champions, that neither team will be able to use and picks five champions for their own use in the game. Once each player has selected their champion, play can begin.

Each champion has five champion-specific abilities, including one passive ability and one ultimate ability, which unlock and become more powerful as the player gains experience by killing enemies. An ultimate ability is generally a champion's most influential tool with the longest cooldown of any of their abilities. Each player also has two non-champion-specific summoner spells, which are useful abilities that take a long time to recharge but are available from the start of the game. The time it takes an ability or spell to recharge is called its cooldown time. Finally, to boost a champion's strength, a player can buy items with gold earned by killing enemies and neutral monsters.

Like on traditional sports teams, each player has a role: attack damage carry, support, mid laner, jungler, or top laner.

3.1.1 Attack Damage Carry

The attack damage carry (ADC) is typically weak early on in the game, necessitating the help of their support to amass gold and experience, known as farming, by killing enemies and non-player characters (NPCs) quicker than their opponents without dying. As the game progresses, however, the ADC can become the most powerful player on the map, carrying their team to victory. The champions used for this role most often use ranged attacks so that they can stand behind their more durable teammates while still dealing damage to the enemy team.

3.1.2 Support

The support (sup) accompanies the ADC in the bottom lane but may also leave their lane more often than their lane partner to help other teammates. The sup's goal early on is to ensure their ADC stays alive and outperforms the opposing ADC. They are also expected to place most of the team's vision wards, allowing teammates to see enemies and objectives on the minimap. Champions chosen to play sup can satisfy a range of needs depending on the rest of the team's composition and the opponents' champions. Some common strengths of support champions include the ability to tank or take a lot of damage in order to protect teammates, the ability to trap or stun enemies, or the ability to heal allies.

3.1.3 Mid Laner

The mid laner (mid), like the ADC, is focused on outperforming their lane opponent early. They may roam to other lanes or help the jungler take an objective, since they are the laner with easiest access to the rest of the map. The most common champions for mid are mages, or champions with ranged abilities and attacks to add to the ranged damage of the ADC.

3.1.4 Jungler

The jungler (jg) is the only player that does not have a position in any one lane. Instead, they travel through the jungle paths between lanes, killing neutral monsters and teaming up on enemies, known as ganking. By keeping tabs on the enemy jg, this player is also able to influence the game by taking objectives far away from their opponent's current position or mirroring their opponent's path to counter-gank, turning what the enemy thought would be an easy kill into a difficult fight.

3.1.5 Top Laner

Early in the game, the top lane is often somewhat removed from the action on the rest of the map, so the top laner (top) focuses on farming and dueling their lane opponent. The champions chosen for top lane are commonly tanks or fighters, meaning they can take a lot of damage in a situation where the main damage dealers need someone to protect them while targeting the enemy.

3.1.6 Team Fights

When fights break out with multiple champions on each side, each player must position themself to make sure that their strengths can benefit their team and their weaknesses do not present their opponents with an opportunity. Correctly timing team fights and positioning, like most aspects of League, requires coordination on multiple timescales. Many minutes before a fight breaks out, the team must begin working to gain as much of an advantage as possible. This entails securing vision around the map, buying items, and positioning around their vision and their teammates so that they aren't separated if the enemy engages. Once the fight starts, coordinating movement such that the team collapses on the enemy together instead of one-by-one is crucial to ensuring no individual player gets ganged up on without any allies nearby to help. On a scale of microseconds, players have to time changes in position and combinations of attacks to capitalize on brief windows of opportunity presented by an opponent taking one step too close or a teammate distracting the enemy's damage dealers. Additionally, each player must be ready to fill a role the moment it is needed. For example, if a tank is dangerously low on health, a damage dealer may need to step in and take some damage while the tank retreats. These momentary role swaps are entirely situational. Every player must constantly be weighing their options and communicating with their team to ensure tight coordination and avoid costly missteps.

3.2 Modes of Communication

The team consistently uses two modes of communication to distribute temporal knowledge: text chat and voice chat. Each has its own constraints and affordances, and each lends itself to different uses.

Text chat allows a player to press “enter,” type a message, and press “enter” again to print that message to the on-screen chat log, where it will stay for the rest of the game. Each entry in the log is automatically timestamped, so if a player can take their hands off of the mouse and ability keys the moment they see an opponent use a summoner spell, they can simply type the opponent’s champion or role and the spell name to communicate the onset of the cooldown timer. Memorizing the cooldown timers of the major spells is a requirement of the players from early in their careers. This combination of storing the cooldown onset time in the chat log, and cooldown duration in each player, gives the team the ability to expend minimal in-game time recording maximal information about its opponent’s time-based resources.

To facilitate efficient storage, the team uses a shorthand for this precise situation. In this shorthand, each role, champion name, or spell can be represented with one to three letters, allowing the players’ fingers as little time away from the controls as possible. If, using this shorthand, a player is storing an enemy spell cooldown in the chat log but does not specify which spell the enemy used, the Flash spell, which instantaneously displaces that champion’s position, is implied. So, if the support and ADC are engaged in a fight, and the support types “ad,” their teammates know that the enemy ADC has no Flash until five minutes after the timestamp next to that message. When the support gets a break from the action, they are expected to retype the information with the end point of the cooldown timer added for future reference; if they originally typed “ad” at 20:03, when they are no longer under pressure they type “25:03 ad f,” which means “the enemy ADC has no Flash until 25:03.”

This redundancy ensures distribution of knowledge that could, at any point, be useful to any part of the team.

If, however, they cannot afford to take their hands off the controls, they call out the role or champion and the spell used and remember the associated time. After the action plays out, they transfer that information from memory to the chat log for less temporary storage and broader team access. Vocal communication allows the convenience of not leaving the controls and the flexibility of spoken language at the cost of permanence. Its strengths are most evident in two contexts:

(1) chaotic team fights, where improvising coordinated attacks and defenses may have to happen in under a second as evidenced by the following exchange over the course of a few seconds in a three-on-three fight that resulted in three kills and zero death for the team:

> ADC: Reksai's here. [an enemy champion appeared making it 2 against 3 in the bot lane] Sup: That's fine.
>
> Jg: I'm coming bot [to make it a 3 against 3 fight]. I'm coming. 5 seconds. I still have jump. [Jg jumps to attack]
>
> Sup: Turn Trundle next, turn trundle next. [directing allies to focus on a particular enemy champion]
>
> Jg: Tank now! [3 kills for 0 deaths, bottom lane counter-gank]

In the chaotic, improvised team fight, the jungler uses vocal communication to indicate how long until he reaches the fight, the status of his strongest engage ability's cooldown, and the precise moment when he wants the support to start absorbing damage for him while they fight the enemy champions, Reksai and Trundle. The support also plans their next target to coordinate the timing of their attacks – all in the span of a few seconds. The ability to make and execute these calls on this time scale simply does not exist with text chat.

(2) Long term strategizing when the team cannot waste time typing out their plans for later reference. In this instance, the support's planning takes place over about 15 seconds:

> We have a late game comp. We just need to take one objective at a time and reset. Vision before objectives guys. OK. Everyone listen up. This is what we're gonna do: get vision in this entire jungle [marks the west jungle], and then go for dragon.

As is evident in the first quote, that is more than enough time for an opponent to show up and engage in a fight. Even without any enemies nearby, the support must constantly be ready control his champion to farm gold and experience, maintain visibility of key areas of the map, or come to a teammate's aid. With these demands on his time, the support cannot afford to let go of the mouse for 15 seconds to type up a schedule. These macro play timing decisions guide the team's actions so completely that, once heard and understood, it is assumed they will never need to be repeated in their entirety, because they are ever-present and salient in the players' memories. If a part of the team acts incongruously with the agreed upon strategy, another will repeat the relevant information to correct the team's course as soon as they notice a deviation from the plan. Delaying the progression of the overall strategy could render it useless if the opponent takes advantage of the team's lack of coordination.

3.3 Information Storage

Certain kinds of temporal knowledge are always stored and communicated in the same ways. Much of this structure is rigid because of both the characteristics of different modes of communication and the nature of how the game presents information. For example, the time until an enemy arrives at a specific point on the map is always communicated through voice (e.g. "Ori's 20 seconds away."). Vocal communication is ideal here for two reasons: (1) the information is only accurate for a short amount of time, and (2) if enemy distance is relevant, the situation is likely dangerous, and voice requires no deviation from controls. The storage location will necessarily depend on whether the enemy is visible when the player performs their estimation. If so, the player communicates information that is partly stored in the on-screen minimap (enemy starting point) and partly remembered (enemy speed of travel). If the enemy is not visible, the player must first work from the enemy's last known position on the minimap to estimate their current position, and only then can they combine starting point with speed to estimate and communicate the opponent's travel time. While based on information that originated on the minimap, all of the knowledge required for the final estimation relies on the player's memory. Last known location is first transferred from the minimap to memory before the player knows if it will be useful. They then combine it with their knowledge of likely paths, and how quickly that champion – with particular items – will travel those paths, to produce an estimate that the team will rely on until the enemy reappears. A long estimate can get the team killed when the enemy appears ahead of schedule. A short estimate can force the team to retreat unnecessarily before securing an objective for fear of an incoming enemy that is actually still far off. Accurately storing time-related information in memory is therefore a vital skill for every member of the team, and trust in each member's ability is a prerequisite of the system for accurate storage, estimation, and communication to be worthwhile [14].

Best practices for storing and communicating different kinds of temporal knowledge, however, are not always adhered to. While the team's protocol calls for enemy summoner spell cooldowns to be recorded in the chat log, players sometimes store them in memory instead. Part of each laner's assortment of temporal information they are responsible for maintaining for the team are their lane opponent's summoner spell cooldown timers. This knowledge directs the team in deciding when to engage or disengage, when to gank, how to position, who to target, and when to attempt neutral objectives. Its accuracy and availability to the team can determine the outcome of a game. For example, after a fight in which the enemy ADC, Ashe, used flash and heal and the enemy mid, Oriana, used flash, the top laner typed 16:40 ad h, 19 mid into the chat log and copied it for later use. The following voice dialog occurred less than a minute later when the enemy team grouped up to siege the middle inhibitor turret:

> Top: Ori no flash. Ashe no flash. Mid: Oh? Ashe no flash? Top: Yeah Ori flashed and ulted me, I said! Mid: Ashe though. Top: Oh yeah. [pastes 16:40 ad h, 19 mid in chat log] I don't know the AD flash time though.

Failure to log summoner cooldowns in text chat is a breakdown in distribution that results from a part of the system treating all knowledge immediately accessible to it as knowledge immediately accessible to the whole system. In the exchange above, the top laner believes he is reiterating known information ("Ori no flash. Ashe no flash.") that he had already distributed throughout the team via text chat. In fact, he had only shared some of his knowledge of the enemy cooldowns, then mistakenly assumed all of the relevant knowledge was allocated to the parts of the system that could use it. Had he not ensured distribution by voicing the information, it would never have made it to the other players. It was, however, still too late. Afraid of engaging the enemy ADC with flash available, the team had stayed out of range and allowed the opponents to damage their inhibitor turret. That weakness in their base could later be exploited in a push from the enemy to end the game.

3.3.1 Individual Responsibility

In order for the team to be confident in its ability to keep track of all the important temporal factors during play, each role is responsible for maintaining knowledge of certain pieces of information. This structure is often quite rigid during the early phases of the game when laners leaving their lanes is rare. At this point, the top and mid laners are responsible for storing – and communicating when necessary – knowledge of their respective lane opponent's summoner spell cooldown timers, ultimate ability cooldown timers, projected time until next level, and travel time to another lane if they leave their own lane to gank. Since ADC and support share the bottom lane, they are both expected to keep track of time-based information about the enemy ADC and support, but ultimately responsibility falls to the support, freeing the ADC to focus more on farming gold and experience. The support is therefore responsible for maintaining knowledge of the enemy ADC and support's summoner spell cooldown timers, ultimate ability cooldown timers, time to next level, and travel time to other lanes. The jungler's chief responsibility is to keep track of the enemy jungler. While this does not at first seem like a temporal task, consider that the enemy jungler is rarely visible. To track their position a player must use knowledge of how long their champion takes to kill each jungle monster, how long it takes their champion to travel each path in the jungle with their current items, how long it takes their champion to reach each level, and how quickly their champion regenerates health and mana with their current items. The jungler must then update that knowledge in accordance with the passage of time on the game clock and factor in as much new information as they can acquire each time the enemy jungler is visible. On top of that, they are responsible for storing and communicating the enemy jungler's summoner spell and ultimate ability cooldown timers. Maintenance and communication of these specific pieces of information is vital for avoiding situations where a subset of the team is outnumbered and overpowered by the enemy.

3.3.2 Information in Flux

As champion statistics change because of increasing levels and items, so too must time estimations based on those statistics. Accordingly, an understanding of how much time an objective will take with the given team composition at the given levels and with the given items allows on-the-fly strategizing with minimal wasted time planning. In the nine words that comprise the dialogue the following conversation between the ADC and mid laner, the players agreed on a schedule of plays for the next three to five minutes that would net the team two buffs and a comfortable lead in gold and experience with which they could overpower the opposing team for the rest of the game:

> ADC: Alright, herald [a neutral monster]? Mid: Yeah, dragon [another neutral monster] after. ADC: Herald, reset, drag [short for dragon]. Mid: Yeah.

While two other teammates are chasing the enemy support to secure the kill, the ADC suggests the next play: taking herald. The mid laner, who has been the main shot caller this game, confirms and adds another play thereafter. The ADC then clarifies the exact schedule they just created, and the mid laner confirms the full plan. Herald and dragon are NPCs that give the team that kills them an advantage, like damage or movement speed increase.

The quick recognition that they could enact this plan before their opponents had enough time to recover from the last fight demonstrates tracking and storage of predictions. Predictions are necessary when planning because they must consider how long it will take the team to finish objectives at their current strength. The only access they have to that information is in the form of their own estimates based on team composition, levels, and items. The levels and items of the team, though, are always in flux as the game progresses, necessitating constant updates to those estimates. Without that prerequisite tracking of personal estimates, the team would have had to spend more time planning and might have missed their window entirely. Two individual players maintaining their own running estimates made it possible for the team to decide upon a plan with little additional effort; the decision needed no explaining, since the two agreed, and the rest of the team was free to focus their attention on getting a kill.

3.4 Summary

Where temporal knowledge is stored and how it is communicated – how knowledge of time is distributed – in an elite LoL team is a question of what parts of the system need access to the information, what timescale the information belongs to, and how free the player or players with access to the information are to make it available to the rest of the team. Each player and artifact maintaining internal representations of the passage of time also marks important points in time externally. This affords the team confidence to make aggressive plays and elicits appropriate caution when necessary. It also allows the team a level of coordination at a fine temporal granularity for both split-second tactics and long-term strategies.

Chapter 4

Empirical Study

4.1 Introduction

How we interact in teams is how we do collaborative and cooperative cognitive work. Teams communicate to establish common ground [17], to build trust [91], to distribute information [61], to coordinate [13], to strategize [28]. Communication is, in fact, in the very definition of interactive team cognition [18]. How teams communicate is known to relate to how they perform in a variety of contexts. The teams research literature is rife with examples in different domains. There are even examples of intervention research where findings regarding communication practices from one domain have been adapted and successfully employed in another domain that ostensibly shares little with the original context. These teams, however, share crucial characteristics [13].

There are also many different team taxonomies used to categorise different kinds of teams and team tasks (e.g. [70], [102], [25], [111]). None of these taxonomies, though, are built on findings about practices that are evidenced as successfully transferring between teams within a taxonomic category. Similarly, the previously mentioned intervention studies that have successfully transferred team cognitive practices across domains have not discussed their results in terms of any existing team taxonomies. See chapter 5 for a detailed exploration of a category of teams across disparate domains that share such characteristics with the esports teams described in this dissertation.

This study focuses on team communication practices in a specific domain, competitive *League of Legends* (LoL), that has the potential to produce findings relevant to teams in disparate domains, as discussed in chapter 5. I explore relationships between experience – both in gameplay and in teamwork – and aspects of team communication that apply to awareness, coordination, and in-game mentoring when they are most difficult and most critical: during high pressure periods of play that influence the outcome of the game. This expert-novice comparison helps to uncover characteristics of team communication displayed by players and teams at different levels of competitive performance. How a team communicates under pressure may well determine that team's performance or even their ability to learn from experience, regardless of domain. If esports provide a context for examining teams more broadly, understanding the differences in communication practices between expert and novice LoL teams can help us develop and test similar practices in teams under similar pressures.

4.1.1 Research Questions

These research questions frame this work in terms of specific aspects of communication across levels of expertise in teams. Communication is specifically examined in terms of frequency, style, and task-oriented information, all of which are defined and operationalized in the following methods section. Expertise is specifically examined in terms of both a team's experience working together and a team's experience with a specific task, both of which are operationalized in the following methods section.

RQ1: How does team communication differ in terms of frequency, style, and information shared in expert and novice teams?

RQ2: How do patterns in team communication relate to performance in expert and novice teams?

To explore these questions, this 2 x 2 factorial design tests relationships between in-game communications in LoL teams that vary in both experience as a team and experience with the game. This study identifies how the content, style, and amount of communication differs between novice and expert teams; whether those differences relate to experience with the game, experience as a team, or both; and whether experience-based differences in communication relate to how teams perform in stressful in-game situations.

4.2 Methods

4.2.1 Periods of Interest

To measure communication and performance as they relate to critical in-game events, I focus data collection and analysis around contested in-game objectives (e.g. Dragon, Herald, Baron) and team fights during laning phase (i.e. before the first turret falls). These are moments during play that can strongly influence a game's outcome, and are therefore high pressure moments in which teams require superior attention management and coordination to outperform their opponents and gain an advantage. These periods of interest (PoI) begin when the play is first communicated about by any player on the team and end 30 seconds after players stop taking or dealing damage. The 30 seconds after the final damage exchange are included in each period to ensure inclusion of any post-play debrief or related communication. The transcription of each PoI includes all team communication for that entire duration.

4.2.2 Pariticipants

The goal for recruitment was to meet statistical power requirement for analyses described in the Findings section. Since the number of PoI's per game can be unpredictable, I designed the study to exceed the necessary sample size for these analyses. To run three data collection sessions per group, with two teams of five players participating in each session, recruitment was focused on recruiting six teams (30 players) per group (N = 120, table 4.1).

These 120 total participants that comprise the 24 teams in this study were recruited through fliers (appendix B, online posts, emails, and undergraduate class announcements. Consent and detailed information were made available online for those interested to review and sign – and for parents or guardians to review and sign in the case of minors. This study was approved by the University of California IRB on October 16, 2020 (HS 2020-5976).

Groups of five participants that agreed to participate as a team were assigned a date and time for their session and invited to the study's Discord server. Individual players who agreed to participate were randomly assigned to teams of players with similar levels of experience with the game as determined by their in-game rank, assigned a date and time for their session, and invited to the study's Discord server. Participants who were randomly assigned to teams were not given information about the team they were assigned to until the session began. Each participant was sent a Polar H10 heart rate monitor, which they kept as part of their compensation.

The team experts (TE) in table 4.1 are defined as groups of five players who have played at least ten LoL matches together in the month prior to their study session. Their actual total games played together ranged from 10 to 500 (table 4.3). Team novices (TN) are groups of five players who have never played together before. The game experts (GE) in table 4.1 are defined as players with in-game LoL ranks of Gold or higher. Game novices (GN) are players with ranks of Bronze or Silver (figure 4.1). In the total population of ranked

Table 4.1: Sample of teams stratified by two factors: team expertise and game expertise.

	Game Novices (GN)	Game Experts (GE)
Team Novices (TN)	6 TNGN teams	6 TNGE teams
Team Experts (TE)	6 TEGN teams	6 TEGE teams

Table 4.2: Gender and age descriptives by group.

Group	N	Female	Male	Non-binary	Age Mean	Age SD	Age Min.	Age Max.
All	120	12	103	5	20.87	2.09	15	25
TNGN	30	3	25	2	20.70	1.86	18	25
TEGN	30	6	23	1	19.33	2.59	15	24
TNGE	30	1	27	2	21.50	1.71	18	25
TEGE	30	2	28	0	21.80	0.96	20	24

LoL players, the top 34.3% are ranked Gold or above, the bottom 4.8% are ranked Iron, and the remaining 60.9% are ranked Bronze or Silver [89]. As an example of how these different factors of expertise interacted to define the four groups, a TEGN team is a group of five players ranked Bronze to Silver who have played at least ten matches together. The distribution of ranks by group are reported in table 4.4 and table 4.1.

As noted in table 4.2, 103 (85.83%) of these participants identified as male, 12 (10.00%) as female, and 5 (4.17%) as non-binary. Their ages ranged from 15 to 25 years of age (M = 20.83, SD = 2.09). The game experts in this sample were, on average, significantly older (M = 21.67 years, SD = 1.41) than the game novices (M = 20.03 years, SD = 2.36) $t(119) = 4.60$, $p<0.001$. There was no significant difference in age between team experts (M = 20.57, SD = 2.30) and team novices (M = 21.17, SD = 1.83) $t(119) = 1.58$, $p=0.12$.

Table 4.3: Team experience: self-reported games played together by group.

Group	Games Mean	Games SD	Games Min.	Games Max.
TNGN	0	0	0	0
TEGN	60.43	102.07	10	500
TNGE	0	0	0	0
TEGE	124.20	158.61	10	500

Table 4.4: Game expertise: in-game ranks by group.

Group	Bronze	Silver	Gold	Platinum	Diamond	Master	GM	Challenger
TNGN	12	18	0	0	0	0	0	0
TEGN	10	20	0	0	0	0	0	0
TNGE	0	0	11	8	8	2	0	1
TEGE	0	0	14	3	12	1	0	0

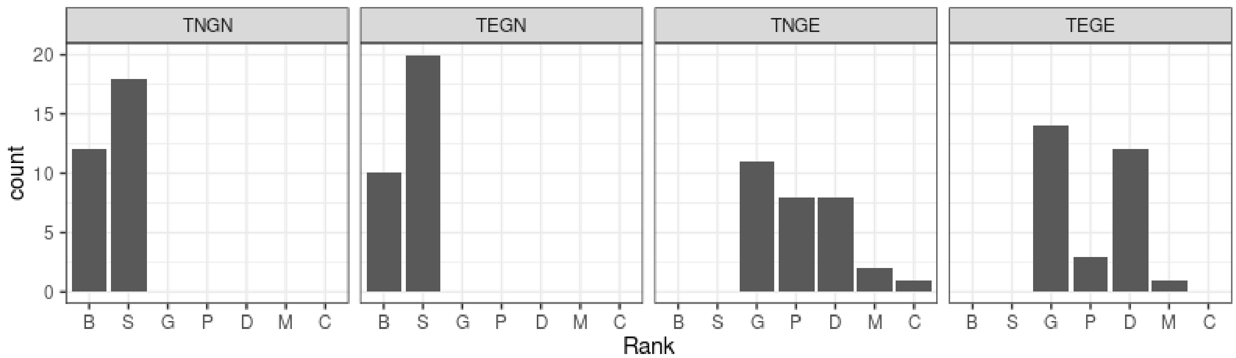

Figure 4.1: Bar graphs of rank distribution by group.

4.2.3 Data Collection

Once the research team briefed each participant, made sure the data collection software was correctly installed on their computer, and checked that their webcam, microphone, and Polar H10 heart rate monitor were all working properly, each session began with a pre-session survey collecting information on demographics, game expertise, and team experience (appendix C). The items on this short survey include in-game identifier, year of birth, gender, current LoL rank, highest achieved LoL rank, and how many games the participant has played with their teammates.

Each team participated in one data collection session, during which they played three games of LoL against one other team in their group. These match-ups were selected so that the average ranks of the two teams playing in each session were comparable. With two teams playing three games in each session, three sessions per group yields nine games played per group, or 36 played across all four groups. At the beginning of each data collection session researchers confirmed receipt of each participant's signed consent forms and administered the pre-session survey to gather and confirm relevant demographic, team experience, and game experience data (appendix C). As participants completed their pre-session surveys, researchers confirmed participants properly installed the data collection software, CapturEsports [131].

During the matches, CapturEsports recorded each player's game telemetry data, including text chat, pings, and ability casts; each player's screen while they are in game; each player's audio including team communication over Discord; and summative game statistics from each player's account through the Riot API. For a detailed description of CapturEsports, see Yao's thesis on its design, development, and implementation [131]. The researchers assisted with and confirmed upload of these data between games, then gave the teams a five minute break before the next game. After the third and final game of each session the researchers confirmed upload of the final game's data, debriefed participants, and uploaded the recordings containing the verbal communication data. After each session, researchers began identifying and transcribing PoI's using the CapturEsports data, screen recordings, and voice recordings. The timeline of data collection over the course of each session is presented visually in table 4.5.

While far more PoI's were identified than the researchers could reasonably transcribe and code over the course of data collection and analysis, power analyses indicated that a sample size of 160 PoI's yields sufficient power for testing the hypotheses detailed in the Hypothesis Testing section, including for the two-way ANOVAs that test for differences in communication between levels of both team and game expertise. To determine which 160 PoI's the researchers transcribed and coded, I randomly sampled 40 PoI's from the total collection of identified PoI's for each group. None of these sampled PoI's were from overlapping periods of play, ensuring independence of observations for statistical analyses.

Table 4.5: Data collection protocol timeline for each session.

	Pre-Test	Game 1	Break	Game 2	Break	Game 3	Debrief	Post-Session
Survey	X							
CapturEsports Recording		X	Upload	X	Upload	X	Upload	Identify PoI's
Voice & Screen Recording		X		X		X	Upload	Transcribe PoI's

4.2.4 Data Analysis

With the corpus of 160 PoI's identified, transcribed, and prepared for analysis, the researchers coded those transcriptions in terms of a pre-determined coding scheme describing communication frequency, style, and content. I supply justification, definitions, and examples of these *a priori* codes in the following Coding Scheme subsection. See appendix D for an example of a coded PoI. I then describe the process used to establish inter-rater reliability and report on the effectiveness of that process in the Inter-Rater Reliability subsection. The final subsection under this Data Analysis header, Hypothesis Testing, details the hypotheses determined before analysis, tested during analysis, and reported on in the Findings section.

Coding Scheme

Marlow, Lacerenza, & Salas [81] identify communication frequency as one of three aspects of team communication that have the most impact on emergent states and team outputs. In previous exploratory work [96], I found preliminary evidence for a relationship between how many pieces of temporal information communicated by a LoL team during the first offensive play of a game and the result of that play as measured by kills and deaths. Those results came from only one expert team's games during a collegiate national championship and are far from conclusive. The present study tests that relationship to better understand how the amount of team communication around a given play might relate to the team's performance. There are still open questions around how much communication expert and novice LoL teams can benefit from, how communication frequency can change under pressure, and how much communication might be too much and result in vital information being lost in chaotic chatter.

In their study of how peer mentoring can contribute to academic success, Leidenfrost, Strassnig, Schabmann, Spiel, & Carbon [74] identified three styles of mentorship: motivating master mentoring, informatory standard mentoring, and negative minimalist mentoring. The motivating master mentors sent their mentees messages that were both motivational and informative, and they sent very few negative messages. The informatory standard mentors sent messages that were much more informative than motivational with very few negative messages. The negative minimalist mentors sent messages that were shorter, carried less information, and were much more negative than those sent by their counterparts who fell into the other two styles.

The mentees in Leidenfrost et al.'s [74] study who performed poorly on the academic pretests were significantly more likely to successfully complete the peer mentoring program than chance would predict if they were mentored by a motivating master mentor. They also reported that they found no significant decrease in program completion rate among mentees who performed well on the academic pretests and were mentored by a negative minimalist mentor. These were, however, the only two hypotheses that Leidenfrost et al. [74] tested regarding relationships between specific mentoring styles and mentee performance, leaving open questions about, for example, the influence of informatory standard mentoring.

If these relationships between peer mentoring styles and mentee performance transfer from academics to other domains requiring more synchrony and tighter coordination in teamwork, we could find a relationship between motivational or informational feedback in LoL teams and their in-game performance or expertise.

To understand in-game communication in LoL teams in terms of Leidenfrost et al.'s [74] styles of peer mentoring, the coding scheme includes a Motivational code for positive, neutral, or negative valence (motivational +/0/-) and an Informative code whether it supplies useful information or lacks substance (informative +/-).

Coding turns of talk for whether they are immediate or delayed (timely +/-) and whether they refer to teammates collectively or single out individual players (collective +/-) allows exploration of alternative means for analyzing team play and team-orientation along the lines of previous team communication research, as opposed to the limited methods currently used in the esports research literature.

The peer mentoring literature converges on these qualities with evaluations of communication in the teams research literature. Each of these four communication style indicators address a part of what Marlow, Lacerenza, & Salas [81] call communication quality. Marlow, Lacerenza, & Salas's framework characterizes team communication in terms of frequency, quality, and content (figure 4.2). They argue that communication quality, "regardless of quantity, leads to a clarification of what and how events and contributions to interdependent tasks should take place, allowing for smoother overall functioning and better performance" [81].

In terms of task-related communication content, my exploration of the distributed cognition of an expert LoL team [96] found that time-related information was of particular focus. Tracking communication of time-related information in that team allowed me to illustrate how the players stored and distributed knowledge and cognitive work as a team. Here I explore how consistent that focus on temporal information is across teams of different levels of expertise. Communication content is the final of the three aspects of team communication highlighted by Marlow, Lacerenza, & Salas [81], and the temporal information I focus on here specifically address what they call "task-oriented interactions." The coding scheme includes a Temporal Information code for whether task-oriented, time-related information

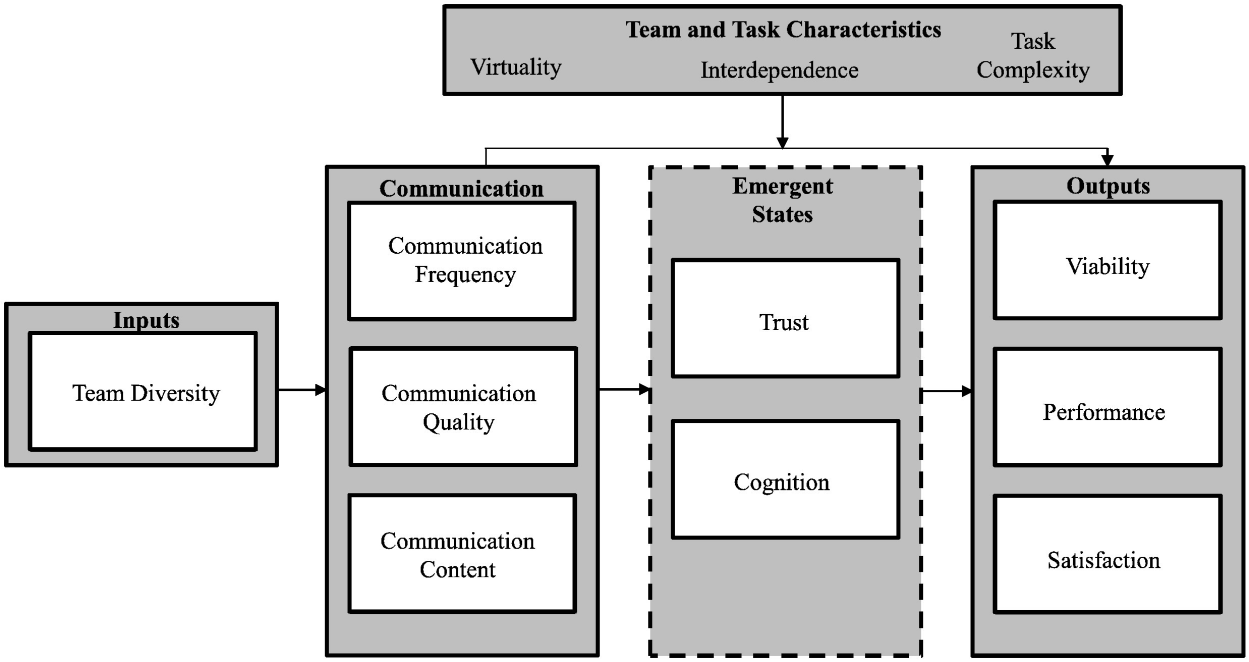

Figure 4.2: Marlow, Lacerenza, & Salas's "Proposed communication process framework in virtual teams." Reprinted from [81].

is included in the content of a turn of talk (temporal information +/-). None of the codes are mutually exclusive, and the only dependency is that ToT's that contain task-oriented temporal information (temporal information +) must logically have an informative style (informative +). See table 4.6 for reference definitions of each code in the coding scheme.

Inter-Rater Reliability

To ensure sufficient inter-rater reliability, the three researchers each independently – and blindly to each other's coding – coded every turn of talk from the same random 10% of the data corpus using the *a priori* coding scheme described in the Coding Scheme subsection. Given the likelihood of raters agreeing by chance when applying codes with only two or three levels, like those in this coding scheme, Percent Agreement can be misleadingly high. Cohen's Kappa (κ) [110] accounts for the likelihood of agreement by chance by calculating the ratio of the difference of the observed percent agreement (P_A) and the expected percent

Table 4.6: Coding scheme table of code definitions.

Code	+	0	-
Motiational	Positive valence	Neutral valence	Negative valence
Informative	Contains or requests useful information or recommends action to take	n/a	Lacks substance
Timely	Future or present tense or referring to future or present event	n/a	Past tense or referring to past event
Collective	"We / you (all)"	No reference to players	"I / you (one)"
Temporal Information	Contains task-related temporal information	n/a	Lacks task-related temporal information

Table 4.7: Strength of agreement for ranges of Cohen's Kappa according to Landis & Koch. Reprinted from [71] (p. 165).

Strength of Agreement	κ *Range*
Poor	<0.00
Slight	0.00 - 0.20
Fair	0.21 - 0.40
Moderate	0.41 - 0.60
Substantial	0.61 - 0.80
Almost Perfect	0.81 - 1.00

Table 4.8: Cohen's Kappa values from the third round of inter-rater reliability testing.

Code	κ
All codes	0.73
Motivational	0.64
Informative	0.71
Timely	0.80
Collective	0.68
Temporal	0.82

agreement (P_c) to the expected percent disagreement ($1 - P_c$):

$$\kappa = \frac{P_A - P_c}{1 - P_c}$$

This step beyond calculating a simple Percent Agreement accounts for the likelihood of raters agreeing by chance. To calculate κ across the three raters, κ is first calculated for each possible pair of raters. The average of those three κ's then yields the inter-rater reliability for the full coding team [51].

The coding scheme's reliance on objective semantic characteristics for some codes and minimal subjective interpretation for others meant that the coding team aimed for at least substantial agreement as defined by Landis & Koch's κ benchmarks reproduced in table 4.7 [71].

After two rounds of training, the third round of inter-rater reliability testing produced results that indicated substantial agreement ($\kappa = 0.73$), as detailed in table 4.8.

Hypothesis Testing

This subsection explicates how constructs named in the research questions are operationalized, describes the various hypotheses constructed to explore the research questions, and reports the statistical methods used to test each hypothesis.

For these analyses, team communication frequency is the number of ToT's per second to account for PoI's of differing durations. Team communication style is examined in terms of four qualities: motivational valence (code: motivational), whether informational content is present (code: informative), verb tense (code: timely), and singular and plural pronoun use (code: collective). Communication content is also further examined for the presence of temporal knowledge, since previous work has identified temporal knowledge as task-oriented information that is heavily emphasized in expert LoL play. Each of the communication quality variables are analyzed as proportions. For the communication quality codes, this proportion is the difference between the number of ToT's containing positive and negative instances of the code divided by the total number of ToT's in that PoI (i.e. (positive - negative) / total). For the task-oriented content code, this proportion is simply the number of ToT's containing task-oriented temporal information divided by the total number of ToT's in that PoI. The possible range for the communication quality codes is therefore -1 to 1, while the possible range for the temporal information code is 0 to 1.

Expert/novice comparisons between teams are made in terms of both team experience and game expertise. Team experts (TE) are defined as groups of five players who have played at least ten LoL matches together, though team experts reported a wide range of games played together from 10 to 500. Team novices (TN) have never played together before and were randomly assigned teammates within their group. Game experts (GE) have in-game ranks of Gold or higher, and game novices (GN) are ranked Bronze or Silver. Team performance is measured in terms of (a) a team's kills during a PoI minus their deaths during that PoI and (b) whether they won an objective, lost an objective, or no team secured an objective during the PoI.

Marlow, Lacerenza, & Salas [81], in their review of virtual team communication research, emphasize frequency, quality, and content as the well-studied features that define team communication. Frequency, according to the literature, does not necessarily predict performance. In other words, more communication over a given period of time is unlikely to yield better results on a team's task as long as the team has established sufficient common ground to coordinate without frequent communication [17]. In fact, too much communication may hinder team performance. In Marlow, Lacerenza, & Salas's [81] words,

> Marks, Zaccaro, and Mathieu [80] highlighted the necessity of distinguishing between communication frequency and other aspects of communication, as a prevalent finding within the literature is that a higher frequency of team communication is not always related to increased team performance; some teams are able to demonstrate effective performance under complex conditions despite limited opportunities to communicate with other team members [31]. Moreover, familiar teams have been found to achieve a higher degree of performance than unfamiliar teams despite exchanging less information [32].
>
> Researchers have suggested that familiar teams are able to perform effectively, even in the absence of overt communication, due to their practiced shared cognition [16] [31]. This understanding enables team members to behave and contribute to the task in a manner that is compatible with their teammates; it further allows team members to understand how other team members may respond to various scenarios, despite being unable to communicate [16]. Consequently, communication frequency is argued to not necessarily be required for high team performance.

H1.1$_0$: There is no significant relationship between the ToT's per second during PoI's and the result of the objective fight in terms of KD.

H1.2$_0$: There is no significant relationship between the ToT's per second during PoI's and the result of the objective fight in terms of objective win/loss.

H1.3$_0$: There is no significant relationship between the ToT's per second during PoI's and team experience.

H1.4$_0$: There is no significant relationship between the ToT's per second during PoI's and game experience.

H1.5$_0$: The frequency of communication is equal across all groups during PoI's.

Researchers see widespread agreement across studies of small teams that characteristics of team communication other than frequency, which Marlow, Lacerenza, & Salas [81] refer to collectively as communication quality, tend to be better predictors of team performance. Research on peer mentoring, a phenomenon central to team development, converged on these specific qualities in Leidenfrost et al.'s [74] identification of three distinct peer mentoring communication styles that had significant impacts on mentee performance: motivating master, informatory standard, and negative minimalist. While Leidenfrost et al. defined these styles based on data in an academic peer mentoring context, their findings still converged on motivational and informative aspects of communication as characteristics vital to team communication quality.

H2.1.1$_0$: There is no significant relationship between the proportion of motivational communication during PoIs and the result of the objective fight in terms of KD.

H2.1.2$_0$: There is no significant relationship between the proportion of motivational communication during PoIs and the result of the objective fight in terms of objective win/loss.

H2.2.1$_0$: There is no significant relationship between the proportion of informative communication during PoIs and the result of the objective fight in terms of KD.

H2.2.2$_0$: There is no significant relationship between the proportion of informative communication during PoIs and the result of the objective fight in terms of objective win/loss.

Marlow, Lacerenza, & Salas's review [81] also highlights communication timeliness as "particularly salient to virtual team interaction," and they note that there is a lack of research on communication timeliness in synchronous teams. The extant literature indicates that delayed communication may inhibit team coordination in virtual, asynchronous team, and from those findings, Marlow, Lacerenza, & Salas infer that synchronous teams would see less variance and therefore less impact of communication timeliness on teamwork. Their review, however, only discusses timeliness in terms the gross timescales experienced by asynchronous, virtual teams. If we consider timeliness on a finer scale – operationalized simply as verb tense – variance may be quite high and may relate to team performance. In LoL, where team coordination matters on split-second and broad strategic timescales alike [96], an emphasis on what is currently happening and about to happen may, in fact, influence team performance.

H2.3.1$_0$: There is no significant relationship between the proportion of timely communication during PoIs and the result of the objective fight in terms of KD.

H2.3.2$_0$: There is no significant relationship between the proportion of timely communication during PoIs and the result of the objective fight in terms of objective win/loss.

Esports researchers have previously explored measures of teamwork and team cohesiveness in LoL in terms of statistics like vision score[1] and assists[2], but these can depend heavily on

[1] Vision score in LoL is a function of vision provided by a player for that player's team and vision denied by that player against their opponent's team. Riot Games has not published the precise formula used to compute vision score.

[2] A player earns assists by damaging or debuffing an enemy champion shortly before they die to another player or non-player character, or by healing or buffing an ally shortly before they kill an enemy champion.

the in-game characters drafted by a team for each game. Teams with more characters that can move through walls, for example, are likely to have much higher vision scores afforded to them by more freedom of movement through enemy territory on the map. Teams with more characters that can shield, heal, and buff their teammates are likely to have far more assists in fights as a result of many characters not having to deal damage to enemies to earn assists. The collective quality of team communication – operationalized simply as singular or plural pronoun use – is an exploratory means for understanding this likely vital, but as of yet difficult to measure, aspect of teamwork.

H2.4.1$_0$: There is no significant relationship between the proportion of collective communication during PoIs and the result of the objective fight in terms of KD.

H2.4.2$_0$: There is no significant relationship between the proportion of collective communication during PoIs and the result of the objective fight in terms of objective win/loss.

More specifically than the informative quality of communication, previous work [96] identified temporal information as particularly highly valued in elite LoL play. Who attends to what temporal information, how that knowledge is stored and shared, and when players communication that information are all aspects of team cognition in LoL that these teams emphasize in practice and utilize in performance.

H2.5.1$_0$: There is no significant relationship between the proportion of temporal information communicated during PoIs and the result of the objective fight in terms of KD.

H2.5.2$_0$: There is no significant relationship between the proportion of temporal information communicated during PoIs and the result of the objective fight in terms of objective win/loss.

Testing for relationships between communication style and team experience, as well as communication style and game expertise will begin a foundation of findings about how these teams communicate and work together at varying levels of expertise. Describing any differences in communication style between novice and expert teams informs conversations of team development and training. These hypotheses taken in tandem with the hypotheses regarding relationships between communication styles and performance at different levels of expertise highlight likely areas of focus for team development research and practice.

H3.1.1$_0$: There is no significant relationship between motivational communication and team experience.

H3.1.2$_0$: There is no significant relationship between informative communication and team experience.

H3.1.3$_0$: There is no significant relationship between timely communication and team experience.

H3.1.4$_0$: There is no significant relationship between collective communication and team experience.

H3.1.5$_0$: There is no significant relationship between temporal information communicated and team experience.

H3.2.1-4$_0$: There is no significant relationship between motivational, informative, timely, or collective communication and game experience.

H3.2.5$_0$: There is no significant relationship between temporal information communicated and game experience.

H3.3.1-4$_0$: The proportion of motivational, informative, timely, or collective communication is equal across all groups.

H3.3.5$_0$: The proportion of temporal information is equal across all groups.

Regardless of whether there are significant differences between communication styles of expert and novice teams, understanding whether these different communication styles relate to team performance will provide actionable insights for teams of all stages of development.

H4.1.1-4$_0$: There is no significant relationship between motivational, informative, timely, or collective communication team performance in terms of KD within each group.

H4.1.5$_0$: There is no significant relationship between temporal information communicated and team performance in terms of KD within each group.

H4.1.6$_0$: There is no significant relationship between the ToT's per second during PoI's and team performance in terms of KD within each group.

H4.2.1-4$_0$: There is no significant relationship between motivational, informative, timely, or collective communication during PoI's and team performance in terms of objective win/loss within each group.

H4.2.5$_0$: There is no significant relationship between temporal information communicated during PoI's and team performance in terms of objective win/loss within each group.

H4.2.6$_0$: There is no significant relationship between the ToT's per second during PoI's and team performance in terms of objective win/loss within each group.

4.3 Findings

The analyses and results in this section deal with differences in team experience, game expertise, performance, communication frequency, communication quality, and communication content. To reiterate what precisely these tests are analyzing, team novices are teams that have never played together before, while team experts have played together at least ten times in the past month; game novices are teams on which all players are ranked Bronze or

Table 4.9: Table of PoI descriptives for the entire corpus.

Variable	Min.	1st Qu.	Mean (SD)	Med.	3rd Qu.	Max.
ToT's / second	0.1	0.2	0.3 (0.1)	0.3	0.4	1.0
ToT count	3.0	11.0	18.4 (9.8)	16.0	23.0	55.0
Duration (s)	25.0	45.0	62.6 (24.0)	59.5	75.0	160.0
KD (kills - deaths)	-7.0	-1.0	0.2 (2.3)	0.0	2.0	6.0
Motivational	-0.4	-0.1	0.1 (0.2)	0.0	0.1	0.5
Informative	-1.0	0.0	0.3 (0.4)	0.3	0.5	1.0
Timely	-1.0	-0.1	0.1 (0.4)	0.1	0.5	1.0
Collective	-1.0	-0.5	-0.4 (0.3)	-0.4	-0.2	0.4
Temporal Info	0.0	0.0	0.1 (0.1)	0.0	0.1	0.3

Silver, while game experts are ranked Gold and above; performance is analyzed in terms of the result of subtracting a team's deaths over a PoI from its kills over that PoI (KD) and by whether they won or lost an objective during a PoI; communication frequency is turns of talk per second over the duration of a PoI; communication quality is the four different characteristics of team communication defined in the introduction of this chapter (e.g. motivational, informative, timely, collective) as proportions of the total turns of talk in a PoI; and the communication content pertinent to these analyses is the proportion of temporal information shared out of the total turns of talk in a PoI. These qualities of communication are both positively and negatively coded, so the proportions can be represented as negative values if a team communicates using, for example, more negative motivational language than positive. 40 periods of interest were randomly selected from each of the four groups, yielding 160 total periods. These periods ranged from 25 seconds to 160 seconds in duration. To compare periods of such varying lengths, amount of communication must be measured in terms of frequency (i.e. turns of talk per second), and communication quality is measured in terms of proportions (e.g. (positive motivational - negative motivational) / total turns of talk). See table 4.9 for the means and ranges of the continuous variables across the entire data corpus, and see appendix E for a comprehensive list of visualizations of the distribution of each communication variable in each group.

As described in the Data Collection section, randomly sampling PoI's for these analyses controls for a number of factors that could skew these results. The most salient of these is performance. If the sample of periods analyzed for one group contained significantly better performance than those from another group, the reported ananlyses would be comparing unlike measures. The fact that there are no significant differences in KD between the PoI's of each group is a necessary beginning for all of the analyses I report. A one-way ANOVA comparing the mean KD's of each group found no significant effect of group on KD ($F(3,156) = 0.10$, p=0.961).

The hypotheses are presented in order so that the first analyses (H1 hypotheses) deal with performance to establish an understanding of what aspects of team communication are actually related to differences in team performance in this sample before delving into how teams of different levels and types of expertise actually communicate. The H2 hypotheses deal with the data at a high level, without delineating between different levels or kinds of expertise. These H2 analyses do not consider expertise or group at all, therefore describing a high level picture of how the teams in this sample communicate, regardless of expertise. The H3 hypotheses begin to deal with one type of expertise at a time, looking at relationships between either team experience or game expertise and dependent variables. The H4 hypotheses examine interactions between levels and types of expertise, describing associations between unique groups and dependent variables. The results of analyses, however, are presented together with results of analyses of the same dependent variables. For example, the analyses of how each aspect of communication relate to KD performance are presented together, so that as I report each result, I am detailing a more specific and complete understanding of the variable in question. For the sake of brevity, I only discuss the significant results beyond the full corpus analyses.

For the correlation tests in these analyses, I rely on Kendall's τ, a non-parametric rank correlation test. This correlation coefficient is more robust against outliers than the alternatives [104], and many of the communication-based characteristics under investigation are not

Table 4.10: Correlation (τ) between KD and communication frequency and qualities. ($p<0.1$. , $p<0.05$ * , $p<0.01$ ** , $p<0.001$ ***)

Group KD	ToT Freq.	Moti.	Info.	Time.	Coll.	Temp.
All	0.21	0.32	0.09	0.04	0.08	0.11
p	0.007 **	<0.001 ***	0.238	0.608	0.314	0.186
TNGN	0.19	0.65	-0.03	-0.16	0.23	0.03
p	0.249	<0.001 ***	0.830	0.316	0.147	0.858
TEGN	0.06	0.55	-0.23	0.11	0.16	0.22
p	0.691	<0.001 ***	0.153	0.509	0.325	0.169
TNGE	0.35	0.07	0.39	0.19	-0.10	0.31
p	0.026 *	0.679	0.012 *	0.245	0.546	0.054 .
TEGE	0.40	-0.12	0.12	0.14	0.01	-0.02
p	0.011 *	0.479	0.469	0.404	0.936	0.893

expected to be normally distributed, and tests for normality confirm this expectation. The significant, moderate correlation between the proportion of informative communication and the proportion of timely communication across the entire corpus (figure 4.3) also restricts validity of models that include both of these variables. The following analyses, therefore, focus on the characteristics of communication across levels of expertise and associations between those characteristics and performance metrics but not on the predictive power of those characteristics toward performance.

4.3.1 Communication and Performance Results

The ToT frequencies across the entire corpus at first appear to not be normally distributed (figure 4.4, figure 4.5). After removing four outliers, though, ToT frequency passes the Shapiro-Wilk normality test ($W = 0.99$, $p = 0.195$) and presents a more normal distribution.

There is a significant association ($\alpha = 0.05$) between communication frequency and KD performance across all PoI's ($\tau = 0.12$, $p = 0.045$, H1.1), within team novice PoI's ($\tau = 0.20$, $p = 0.039$), within game novice PoI's ($\tau = 0.24$, $p = 0.018$), and most specifically within TNGN PoI's ($\tau = 0.35$, $p = 0.039$, H4.1.6). Correlation between communication

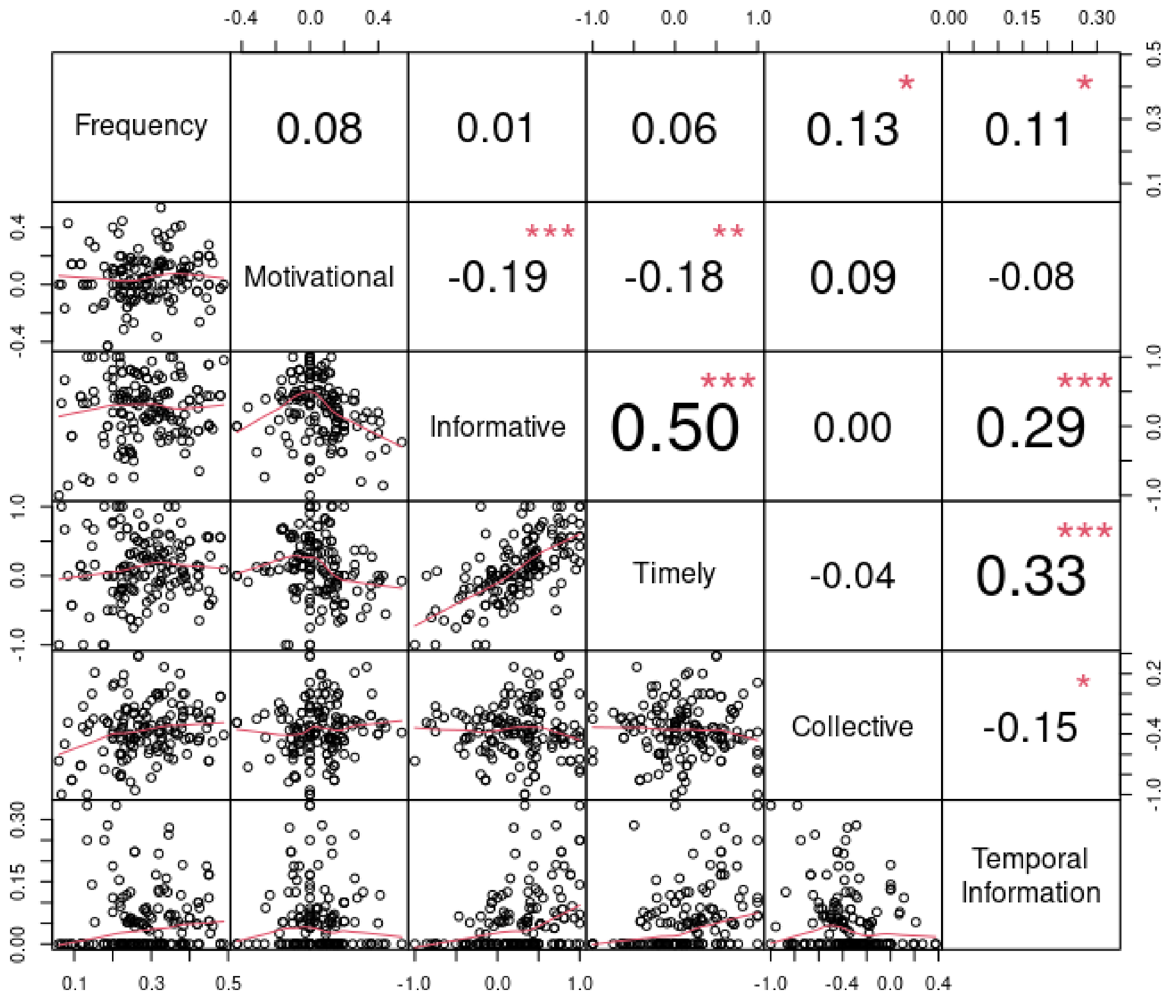

Figure 4.3: Correlation matrix, of communication frequency, motivational proportion, informative proportion, timely proportion, collective proportion, and temporal information proportion. (p<0.1 . , p<0.05 * , p<0.01 ** , p<0.001 ***)

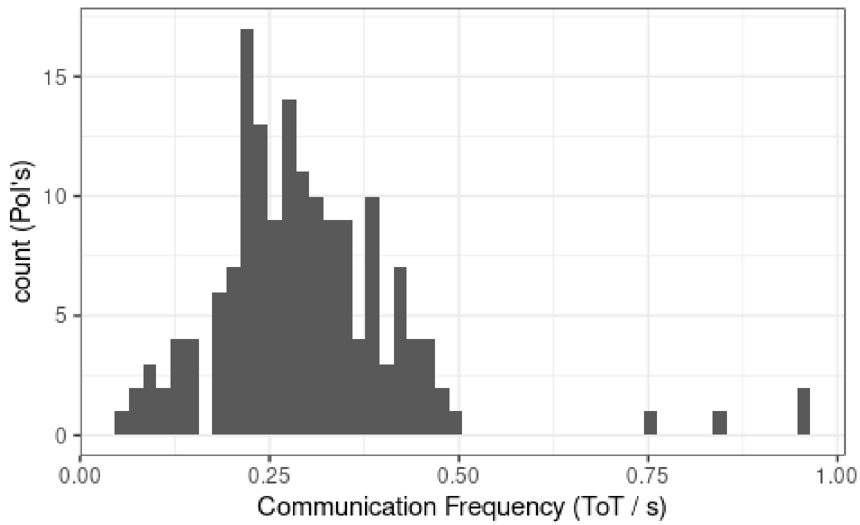

Figure 4.4: Histogram of communication frequency over the entire corpus.

frequency and KD performance in novice teams but not in expert teams of any type aligns well with the literature. The current understanding of communication frequency points to its lack of impact in elite performance. Teams who have yet to work together and have yet to grow deeply familiar with their tasks, however, can still benefit from the development of common ground and team awareness that frequent communication affords them.

Objectives won (n = 66) and lost (n = 44) over the entire corpus are not equal, but there are enough instances of each to satisfy the requirements of a Mann-Whitney U test [78]. There are significant positive associations between communication frequency and winning an objective across all PoI's ($U = 949.5$, $p = 0.008$, H1.2), in team novice PoI's ($U = 225.0$, $p = 0.003$, figure 4.6), in game novice PoI's ($U = 131.0$, $p = 0.010$, figure 4.7), and in both TNGN ($U = 28.0$, p-value = 0.030, H4.2.6, figure F.9) and TNGE ($U = 77.5$, $p = 0.013$, H4.2.6, figure F.9) PoI's. These relationships mostly reflect the relationships between communication frequency and KD performance with the addition of a correlation in TNGE PoI's when looking at objective performance. Team novices at all levels of game expertise are expected, then, to experience an association between amount of communication and performance. In keeping with the literature, teams that have experience working together

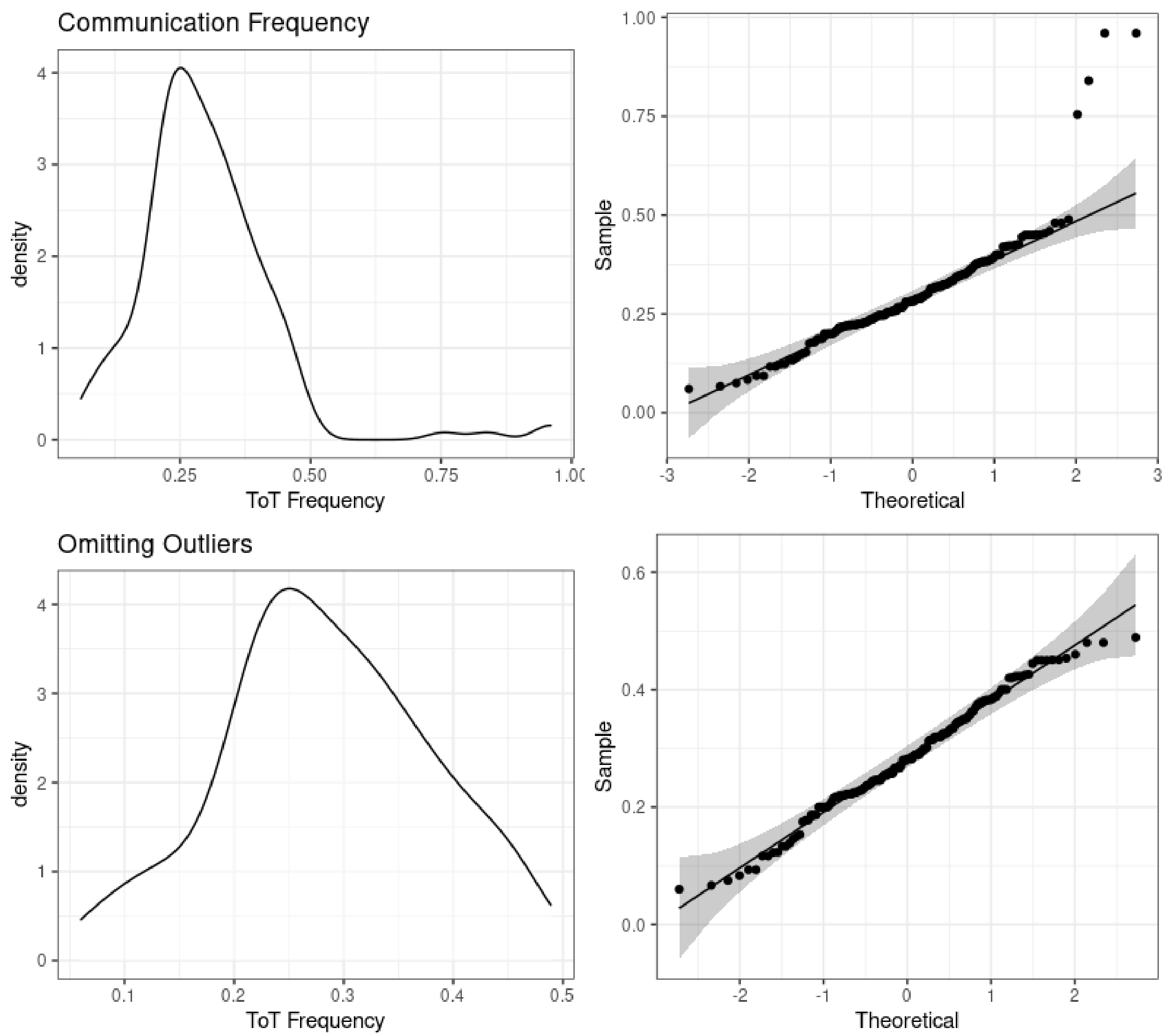

Figure 4.5: Density and QQ plots of communication frequency including and omitting outliers.

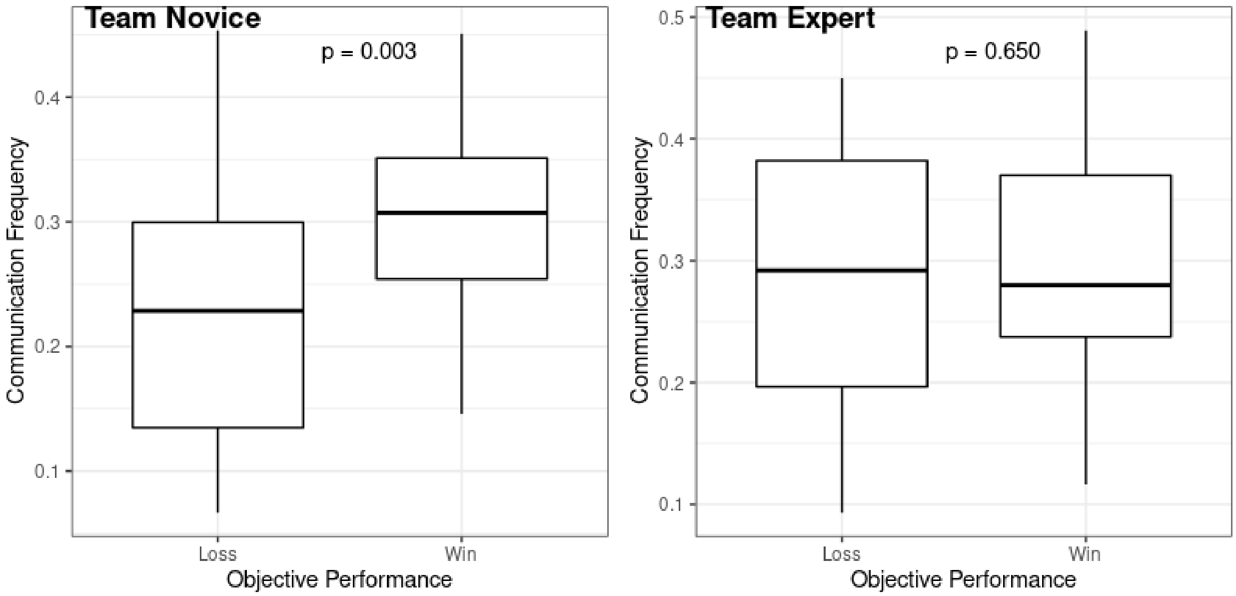

Figure 4.6: Boxplots of communication frequency by objective performance in team novices and team experts.

do not necessarily benefit from communicating more. Instead, it is the quality and content of what they say that is more highly associated with their performance.

Kendall's τ and Mann-Whitney U tests of associations between communication qualities and performance yield a significant relationship for at least some portion of this sample for each coded characteristic of communication.

Motivational communication is related to both KD performance and objective performance across all PoI's (KD: $\tau = 0.23$, $p < 0.001$, H2.1.1; Objective: $U = 1029.50$, $p = 0.010$, H2.1.2), within Team Novice PoI's (KD: $\tau = 0.39$, $p < 0.001$; Objective: $U = 231.50$, $p = 0.004$), within Game Novice PoI's (KD: $\tau = 0.50$, $p < 0.001$; Objective: $U = 126.00$, $p = 0.002$), and more specifically within TNGN PoI's (KD: $\tau = 0.55$, $p < 0.001$, H4.1.1; Objective: $U = 12.00$, $p = 0.001$, H4.2.1). Motivational communication was also significantly associated with KD performance, but not objective performance, in TEGN PoI's (KD: $\tau = 0.29$, $p = 0.016$, H4.1.1). Informative communication is significantly associated with performance among Game Novices (KD: $\tau =$ -0.18, $p = 0.031$; Objective: $U = 0.16$, $p = 0.049$; H2.2.1-2).

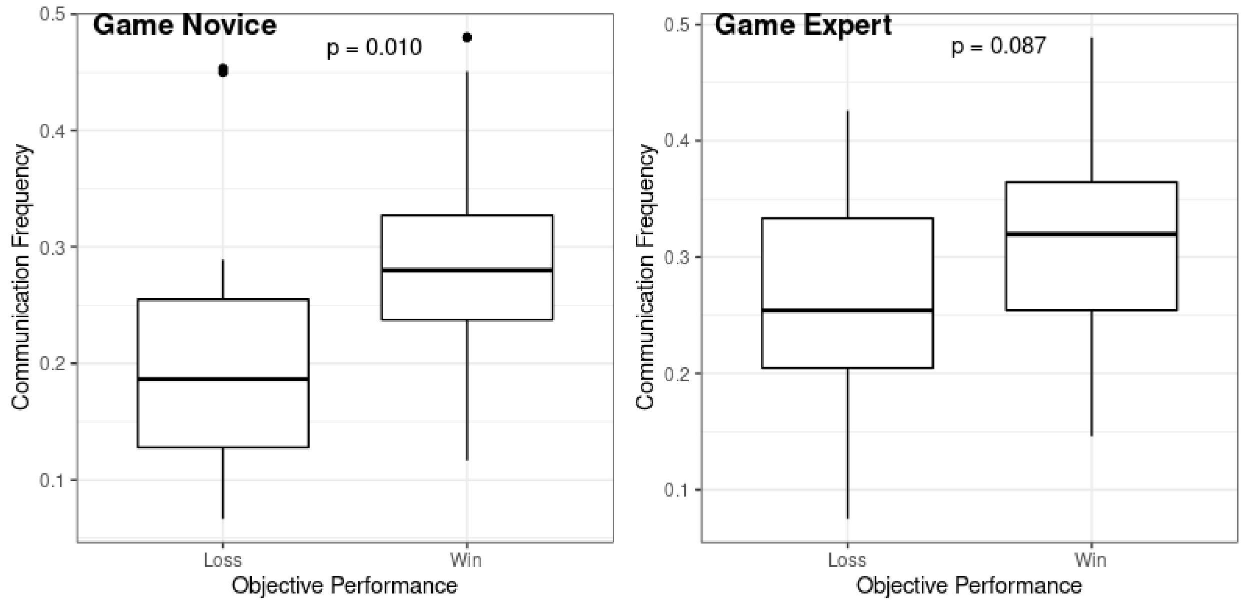

Figure 4.7: Boxplots of communication frequency by objective performance in game novices and game experts.

Timely communication is significantly associated with objective performance, but not KD, for Team Experts (Objective: $U = 202.50$, $p = 0.047$, H2.3.1-2). Collective communication is significantly associated with KD performance but not objectives for Game Novices ($\tau = 0.16$, $p = 0.049$, H2.4.1-2). A comprehensive list of scatter plot visualizations of associations between KD performance and communication variables and box plot visualizations of how communication variables differ between objective wins and objective losses in each group can be found in appendix F.

4.3.2 Communication and Expertise Results

While the results reported in the Communication and Performance subsection suggest styles of communication that relate differently to performance for groups of differing expertise, the following results describe the predominant communication styles those groups display.

Two-way analyses of variance (ANOVA) were performed to test for effects of team experience and game expertise on each of the coded communication variables. Each of these expertise-related factors has two levels, novice and expert, which are defined in the Hypothesis Testing section of this chapter.

There is a significant effect of team experience with communication frequency ($F(1{,}152) = 3.91$, $p = 0.049$, H1.3). This ANOVA yields no significant effect, though, among game novices and game experts (H1.4) or in terms of the interaction between team and game expertise (H1.5). A post-hoc Tukey HSD analysis also finds a significant difference between team novices and team experts ($\alpha = 0.05$). Team experts ($M = 0.30$, $SD = 0.09$) communicate significantly more frequently than team novices ($M = 0.27$, $SD = 0.10$). Means of each of the communication dependent variables for team novices and team experts are listed in table 4.16.

Two-way ANOVAs of the proportion of motivational communication among levels of team and game expertise (table 4.12), the proportion of informative communication among levels of team and game expertise (table 4.13), the proportion of timely communication among levels of team and game expertise (table 4.14), and the proportion of collective communication among levels of team and game expertise (table 4.15) each yield a significant effect of team experience. And each of these results are consistent with post-hoc Tukey tests at an α of 0.05 (H3.1.1-4). Of those four ANOVAs, only the ANOVA test of the proportion of timely information yields a significant result across levels of game expertise (H3.2.1-4), which is also consistent with a post-hoc Tukey test with α set at 0.05. Tukey's HSD test for multiple comparisons found two additional significant differences in motivational communication. Motivational communication in TNGE teams ($M = 0.10$, $SD = 0.16$) was significantly higher than that in both TEGN teams ($M = 0.00$, $SD = 0.14$; $p = 0.023$, 95% $C.I.$ = [0.01, 0.19]) and TEGE teams ($M = 0.00$, $SD = 0.11$; $p = 0.018$, 95% $C.I.$ = [-0.19, -0.01]).

Team experts have significantly more informative ($F(1{,}156) = 16.39$, $p < 0.001$; $M = 0.40$, $SD = 0.36$; H3.1.2) and timely ($F(1{,}156) = 30.09$, $p < 0.001$; $M = 0.30$, $SD = 0.38$; H3.1.3)

Table 4.11: two-way ANOVA of communication frequency as a function of team experience and game expertise.

Source	*df*	Sum of squares	Mean square	*F*	*p*
TeamXP	1	0.03	0.03	3.91	0.049 *
GameXP	1	0.02	0.02	2.39	0.124
TeamXP:GameXP	1	< 0.01	< 0.01	0.09	0.766
Error	152	1.35	0.01		
Total	155	1.40			

Table 4.12: two-way ANOVA of motivational communication as a function of team experience and game expertise.

Source	*df*	Sum of squares	Mean square	*F*	*p*
TeamXP	1	0.35	0.35	14.37	< 0.001 ***
GameXP	1	< 0.01	< 0.01	0.09	0.769
TeamXP:GameXP	1	< 0.01	< 0.01	0.17	0.679
Error	156	3.78	0.02		
Total	159	4.13			

Table 4.13: two-way ANOVA of informative communication as a function of team experience and game expertise.

Source	*df*	Sum of squares	Mean square	*F*	*p*
TeamXP	1	2.77	2.77	16.39	< 0.001 ***
GameXP	1	0.39	0.39	2.28	0.133
TeamXP:GameXP	1	0.13	0.13	0.75	0.388
Error	156	26.41	0.17		
Total	159	29.70			

Table 4.14: two-way ANOVA of timely communication as a function of team experience and game expertise.

Source	*df*	Sum of squares	Mean square	*F*	*p*
TeamXP	1	4.87	4.87	30.09	< 0.001 ***
GameXP	1	0.81	0.81	5.00	0.027 *
TeamXP:GameXP	1	0.01	0.01	0.06	0.807
Error	156	25.23	0.16		
Total	159	30.91			

Table 4.15: two-way ANOVA of collective communication as a function of team experience and game expertise.

Source	*df*	Sum of squares	Mean square	*F*	*p*
TeamXP	1	0.30	0.30	4.58	0.034 *
GameXP	1	0.09	0.09	1.44	0.232
TeamXP:GameXP	1	0.24	0.24	3.63	0.058 .
Error	156	10.24	0.07		
Total	159	10.90			

Table 4.16: Summary statistics of communication frequency and proportions of motivational, informative, timely, collective and temporal information communication by level of team experience

Team Experience	Communication Var.	Count	Mean	SD
Novice	Frequency	80	0.27	0.10
Novice	Motivational	80	0.09	0.18
Novice	Informative	80	0.13	0.46
Novice	Timely	80	-0.04	0.43
Novice	Collective	80	-0.31	0.27
Novice	Temporal Info	27	0.12	0.09
Expert	Frequency	76	0.30	0.09
Expert	Motivational	80	0.00	0.13
Expert	Informative	80	0.40	0.36
Expert	Timely	80	0.30	0.38
Expert	Collective	80	-0.40	0.25
Expert	Temporal Info	55	0.10	0.07

Table 4.17: Summary statistics of communication frequency and proportions of motivational, informative, timely, collective and temporal information communication by level of game expertise

Game Expertise	Communication Var.	Count	Mean	SD
Novice	Frequency	78	0.27	0.10
Novice	Motivational	80	0.04	0.18
Novice	Informative	80	0.39	0.22
Novice	Timely	80	0.06	0.41
Novice	Collective	80	-0.38	0.27
Novice	Temporal Info	32	0.08	0.07
Expert	Frequency	78	0.30	0.09
Expert	Motivational	80	0.05	0.15
Expert	Informative	80	0.31	0.47
Expert	Timely	80	0.20	0.46
Expert	Collective	80	-0.33	0.25
Expert	Temporal Info	50	0.12	0.08

Table 4.18: Summary statistics of communication frequency and proportions of motivational, informative, timely, collective and temporal information communication by group

Group	Communication Var.	Count	Mean	SD
TNGN	Frequency	40	0.26	0.09
TNGN	Motivational	40	0.09	0.20
TNGN	Informative	40	0.06	0.38
TNGN	Timely	40	-0.11	0.40
TNGN	Collective	40	-0.37	0.27
TNGN	Temporal Info	12	0.11	0.10
TEGN	Frequency	38	0.29	0.11
TEGN	Motivational	40	0.00	0.14
TEGN	Informative	40	0.38	0.35
TEGN	Timely	40	0.22	0.35
TEGN	Collective	40	-0.38	0.28
TEGN	Temporal Info	20	0.07	0.04
TNGE	Frequency	40	0.28	0.10
TNGE	Motivational	40	0.10	0.16
TNGE	Informative	40	0.21	0.52
TNGE	Timely	40	0.02	0.46
TNGE	Collective	40	-0.25	0.26
TNGE	Temporal Info	15	0.13	0.08
TEGE	Frequency	38	0.31	0.08
TEGE	Motivational	40	0.00	0.11
TEGE	Informative	40	0.42	0.38
TEGE	Timely	40	0.38	0.38
TEGE	Collective	40	-0.41	0.21
TEGE	Temporal Info	35	0.12	0.08

communication styles than team novices (informative: M = 0.13, SD = 0.46; timely: M = -0.04, SD = 0.43), while team novices use significantly more motivational (F(1,156) = 14.37, $p < 0.001$; M = 0.09, SD = 0.18; H3.1.1) and collective (F(1,156) = 4.58, $p = 0.034$; M = -0.31, SD = 0.27; H3.1.4) talk than do team experts (motivational: M = 0.00, SD = 0.13; collective: M = -0.40, SD = 0.25). Game experts use significantly more timely communication (F(1,156) = 5.00, $p = 0.027$, H3.2.3) and communicate more temporal information (skewed distribution, H3.2.5) proportionally to their total communication. Means of each of the communication dependent variables for game novices and game experts are listed in table 4.17. Post-hoc Tukey's HSD tests also found significant differences in informative communication between TNGN (M = 0.06, SD = 0.38) and TEGN (M = 0.38, SD = 0.35) teams ($p < 0.001$, 95% $C.I.$ = [0.08, 0.56], H3.3.2) and between TNGN and TEGE (M = 0.42, SD = 0.38) teams ($p < 0.001$, 95% $C.I.$ = [0.12, 0.60]); significant differences in timely communication between TNGN (M = -0.11, SD = 0.40) and TEGN (M = 0.22 , SD = 0.35) teams ($p = 0.002$, 95% $C.I.$ = [0.10, 0.57], H3.3.3), between TNGN and TEGE (M = 0.38, SD = 0.38) teams ($p < 0.001$, 95% $C.I.$ = [0.26, 0.72]), and between TNGE (M = 0.02, SD = 0.46) and TEGE teams ($p < 0.001$, 95% $C.I.$ = [0.13, 0.60]); and significant differences in collective communication between TNGE (M = -0.25, SD = 0.26) and TEGE (M = -0.41, SD = 0.21) teams ($p = 0.025$, 95% $C.I.$ = [-0.31, -0.02], H3.3.4). Game expertise is only significantly associated with timeliness of communication, and further work is needed to confirm the potential result of game experts sharing more temporal information (H3.2.5). See table 4.18 for a summary of the means and standard deviations of each of these communication variables for each group.

The distribution of task-oriented temporal information is heavily skewed, and almost half of the PoI's in the corpus contain no task-oriented temporal information at all (n = 78 where temporal information proportion is 0). After removing those PoI's where a team communicated no task-oriented temporal information, this distribution is still heavily skewed (figure 4.8) and remains so after log transforming the data. I report the results of the two-

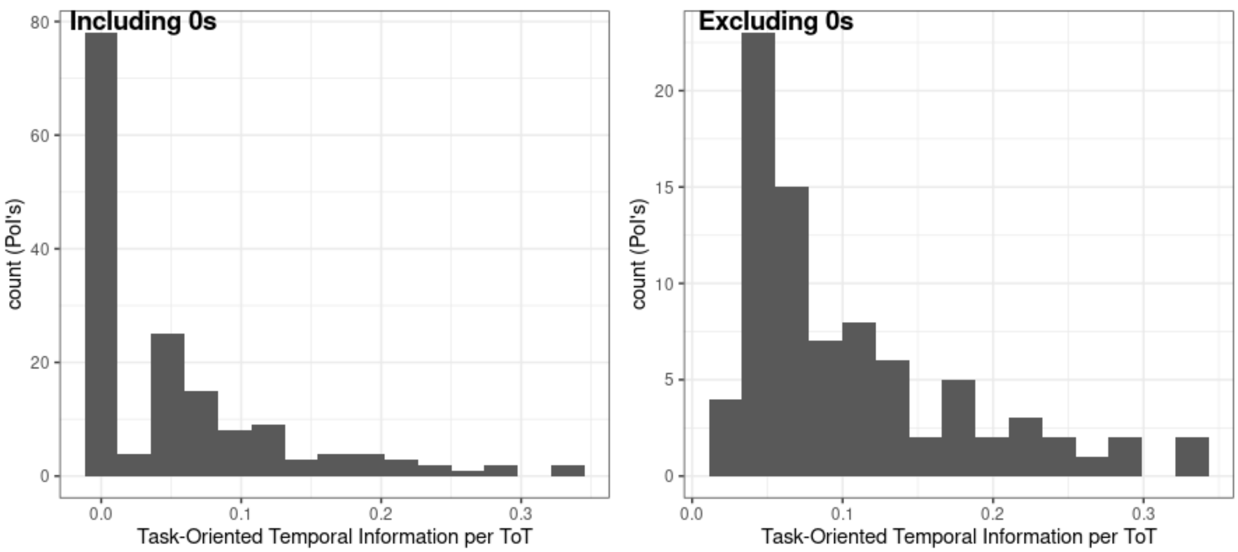

Figure 4.8: Histograms of temporal information communication including 0 values on the left and excluding 0 values on the right.

way ANOVA of temporal information communication in these 82 PoI's in appendix G table G.1 for completeness.

4.3.3 Summary of Significant Findings

This subsection offers a brief, high-level summary of the significant findings detailed in this section. I discuss these findings and how they relate to team communication and team cognition more broadly in the next section.

The TN teams in this sample used significantly more collective and motivational language, while the TE teams used significantly more timely and informative language. The TEGE teams consistently used temporal information, but communicating temporal information was rare or did not happen in other teams.

Communicating frequently and motivationally was significantly related to performance in TN teams. Timely communication was significantly related to performance in TE teams.

4.4 Discussion

These analyses describe how teams of differing levels of team experience and game-specific expertise communicate to manage attention and maintain coordination. Asking these questions of LoL teams provides an example for creating similar profiles of teams in other competitive, cooperative, and collaborative games. The methods presented here for analyzing team communication are also applicable, though, to teamwork in domains beyond video games. Using similar methods to describe and understand the use and impact of communication frequency, quality, and content for teams in disparate domains will allow comparisons across teams working in seemingly varied contexts. Those comparisons will allow researchers to base taxonomic theory on empirical data and provide data-driven insights to teams across fields. If the data of teams in esports and aircraft navigation, for example, are consistent with one another and show consistent effects on team performance, a team in a high consequence domain, like safely navigating aircraft, will be able to benefit from better understanding how experiments performed in a much lower consequence domain, like competitive video gaming, may provide insights for teamwork more broadly. Regardless of the results of this study, these methods establish a means to explore relationships between communication, expertise, and performance at a level of detail not possible without this combination of API data, game telemetry, and screen and voice recordings, and the findings point to opportunities for future work testing communication practices for similar relationships in other domains.

Due to Marlow, Lacerenza, and Salas's [81] well-supported assertion that communication frequency likely impacts performance differently in different frequency ranges and in different kinds of teams, the more specific analyses of relationships between communication frequency are more illuminating than the association found across all PoI's. The potential pattern of team experts communicating more frequently warrants further investigation. The difference seen in these data is not significant, but this is a particular phenomenon that merits further study on its own. Understanding more precisely when communication is too frequent and prone to obscuring teamwork and decreasing performance is a vital problem for teams to explore, especially in domains where not enough communication and too much communication can each cause threats to the safety of patients, passengers, and team members.

Teams with more experience together use significantly less motivational talk. Without rich qualitative data of team members' reasons for and perceptions of motivational communication, why this difference exists is opaque. Potential inferences from these data and teams research literature indicate that it could be because teammates with more experience working together are more likely to have established trust more strongly and therefore feel communicating motivational support to be unnecessary. In teams with less experience working together, that motivational communication could be part of the process of building trust and establishing common ground. In other words, TN teams may be building that trust and establishing common ground by using positive valence communication to identify desired behavior and reinforce teammate relationships, while TE teams already understand the expectations of their task and their team. These analyses, however, do not provide the kind of insights necessary to explain this phenomenon, and these results require rich qualitative work to support and contextualize these inferences.

Teams with more experience together also communicate significantly more information proportionally to their total communication. This difference in how and what teams communicate also implies key differences in why new and experienced teams communicate. While newly formed teams rely on expressing positive reactions without specific information to identify the kinds of behavior they expect of each member and of their coordinated performance, experienced teams focus on distributing knowledge to benefit the team's awareness of the game state. Each member of an experienced team can rely on their understanding of the teams' expectations to guide their behavior, and the team as a whole can trust each member to use information in accordance with established expectations. The better each member – and the team as a whole – understands the current situation, goals, and sub-goals, the better they can align their behavior with their understanding of the team's expected behavior. For a team that has worked together enough to have strong, implicit, shared understanding and expectations of team behavior, then, communicating more information about what is happening in the game – and less motivational judgements of team behavior – provides the necessary context for players, individually and collectively, to act according to team expectations. One team expectation necessarily underlying this behavior is that team members are responsible for collecting and distributing information. How a LoL team goes about this process of collecting, communicating, and acting upon information from the world is discussed in detail in chapter 3. How other teams perform this process has been well-documented for some domains, like in Hutchins's [61] work describing Distributed Cognition in aircraft and naval navigation. Using a similar set of quantitative or mixed methods across domains, however, will be necessary for meaningfully comparing these team cognition and communication behaviors in a way that can lead to findings from one domain generalizing meaningfully to insights for another.

The significantly more timely communication of teams with more team experience supports this inference that team experts are communicating more information with less motivational valence in order to inform their decision-making and coordination by using available information to communicate expectations of team behavior. In other words, TE teams talk about what is currently happening and what is about to happen, while TN teams talk, on average, more about what happened in the past. This timeliness is crucial for both tightly coordinated joint action and for strategizing to prepare for future coordination. The tendency of team novices to fixate more on past activity restricts that ability to coordinate on both short and long timescales. One explanation for team novices' lack of timely communication is that they spend more time talking about what just happened as part of establishing expectations about team behavior in the future. This kind of debrief in experienced teams often takes place after a game, so that the team can manage its attentional resources on performing and strategizing during play, knowing that they will have an opportunity to provide and receive feedback and develop their expectations later.

The use of collective communication was consistently low across all levels of expertise. Among game experts, though, those with no team experience used more plural pronouns than the team experts. While measuring collective communication was posited as a potential alternative to the questionable indicators of team-oriented play used thus far in LoL research, it was only associated with performance outcomes for game novices. It may provide more insight into how teams who have expertise in their task but no experience with their teammates start to build the common ground they need to perform as a collective unit. This process is apparent in TNGE teams' use of more motivational and collective language with lower timeliness compared to TEGE teams. These game experts, then, when faced with the prospect of learning how to coordinate with a new team, work to build trust, common ground, and understanding of expectations by reacting to desired behavior with more positively valenced, collective communication. TEGE teams' much more timely communication points to their already having established that team cohesiveness, freeing their communications to focus on communicating information for coordination in the present moment and for planning for future action.

Game experts communicate temporal information more than game novice teams proportionally to their total communication. This supports Marlow, Lacerenza, & Salas's (2017) identification of task-oriented communication as one of the most influential aspects of communication content for team interactions. These teams have the game expertise necessary to understand, identify, and make use of vital time-related information without lengthy conversation in the midst of critical moments of competition with their opponents.

Teams that have not played together before have much more work to do establishing common ground [17]. This is one explanation for team novices' higher amounts of communication relating to better performance. Teams with experience playing together do not see the same benefits from increased chatter, potentially because their communication is reserved for distributing information about what is currently or what is about to happen. For these teams that have a shared history that they can rely on for common ground and shared understanding of expectations, any additional communication, like motivational talk lacking actionable content, may clutter their communication channels and obscure or delay distribution of critical information.

4.5 Limitations & Future Work

As a presentation of novel methods for and approach to researching team cognition, and as an attempt to build a foundation for generalizable teams science across domains, this study necessarily has many limitations. My argument for this paradigm of team video games as a testing ground for teams in other domains requires much future work before we can reasonably translate findings across domains.

4.5.1 Limitations of the Sample

A major limitation of any sample of a large and difficult-to-census population is the representativeness of that sample. The game experts in this sample are significantly older than the game novices. This relationship logically likely holds in the broader competitive LoL player population, because older players have had longer to develop expertise. There is, however, no way of knowing whether it is, in fact, representative of the entire competitive LoL population without a demographic census. More generally, it is difficult to assess whether the demographics of the teams in each group of this sample accurately represent the makeup of teams at similar levels of expertise in the competitive LoL population. These demographic differences can be impactful when comparing team communication across levels of expertise. This sample ranges in age from 15 years to 25 years, which cover significant developmental changes. It is impossible to know, given these data, whether the differences observed in team communication styles between novices and experts were confounded by the differences in age and therefore cognitive development of the participants.

Further, this sample does not contain enough teams with enough different types of diversity to compare teams with different demographic compositions. There's a substantial body of literature exploring the effects of different kinds of diversity on teamwork in a variety of contexts. These diversity factors range from ethnicity to gender and from language to educational background. Understanding how different kinds of diversity interact with these delineations of expertise and communication patterns in high pressure situations would contribute insights to that conversation that might help explain differences in the work of diverse teams.

More fine-grained understanding of expertise would also improve this work. Team experts ranged from 10 to 500 games played together as reported by the participants. While the experience gained as a team over ten games differentiates a team from a group of players who have never played together, there are likely differences in communication and team cognitive work between a team that has worked together ten times and a team that has worked together hundreds of times. Ten games is enough to develop some common ground and understanding of expectations, but the trust and understanding gained over hundreds of hours playing together is likely observable in how teams communicate, perform, and distribute their cognitive work. Game experts ranged from Gold-ranked, or roughly the top third of ranked players, to Challenger-ranked, or roughly the top 0.01% of ranked players. Similar to the likely gap in team experience, this difference in game expertise is obvious to any observer familiar with the task. While GE teams were matched into sessions with teams of similar average ranks, aggregating team communication data across these disparate levels of expertise loses granularity that may reveal differences in how the most elite teams communicate.

4.5.2 Limitations of the Research Protocol

Adapting a research protocol that was originally meant for in-person observation and data collection into a remote study in response to the COVID-19 pandemic presented unexpected hurdles. The original methods included triangulating periods of interest for analysis based on the gameplay data around objective fights and team fights, which were used, but also based on salivary cortisol levels, which were not collected, and heart rate variability (HRV), which were not used. Identifying PoI's with this combination of gameplay and stress data, and analyzing the changes in stress data, would have allowed for analysis of team communication and stress levels as they relate to and respond to each other. In other words, how teams communicate during stressful periods of play, but also how teams might use communication to mitigate stress during those periods, are both research questions that the original methodology would have focused on. Attention management under stress is difficult work, and understanding how team interactions play a role would have implications for team training toward safety and performance across domains. The collection of saliva for cortisol analysis was not an option during COVID-19 lock-downs when these data were collected. I did send heart rate monitors to participants to wear during data collection along with detailed instructions on how best to wear and operate them, but without in-person guidance and supervision, the HRV data was not collected rigorously enough to be reliable or valid.

Other issues from remote data collection included participants' internet going out during data collection sessions and less ability to help participants troubleshoot software and hardware issues. While I was able to resolve each instance where these problems arose, some data collection sessions spanned upwards of four hours as a result of such issues. The extended duration of some sessions could have contributed to participant fatigue and impacted team communication in the latter games of those sessions.

The lack of qualitative data collection and analysis regarding why teams use different styles of communication leaves many open questions around the inferences drawn from these results. Even whether any of these characteristics of team communication are intentional on the part of teams or individuals is unknown. These findings are most impactful for practitioners if teams can recognize these communication styles in their own work and intentionally change their communication practices. To support that process, research is needed to better understand the common reasons behind the different styles and the best practices for recognizing and altering influential aspects of team communication.

4.5.3 Selecting Periods of Play under Pressure instead of Measuring Stress

The PoI's analyzed in this study are assumed to be high pressure, stress-inducing periods, because of the fights they feature around key objectives. There are many rigorous methods for collecting data on stress that don't require that assumption. This report makes effective use of none of them. The original design of this study brought participants into the lab and made use of both cortisol levels in saliva and HRV to identify PoI's of elevated stress and arousal across the team. The COVID-19 pandemic made it unwise to bring ten participants and a handful of researchers together in person, and saliva collection was out of the question. Reworking the methods to run data collection sessions remotely not only allowed this work to move forward, it also created a study environment much closer to how LoL teams work together in the wild. Each participant received a Polar H10 heart rate monitor to wear during data collection and to keep as part of their compensation for participating. While rigorously collected HRV during play is an illuminating measure of stress and arousal, the combination of participants inconsistently understanding heart rate monitor instructions and lack of other measures of stress made it impossible to infer team stress levels from the collected HRV data. These data were therefore omitted from analyses.

4.5.4 Future Work

The methods developed for this study are designed for use across domains to produce comparable findings in pursuit of generalizability of team communication and team cognition research. Future work conducting similar studies using these methods to describe team communication practices in other domains will test the viability of this methodology. Chapter 5 explains the concept of isomorphism between teams in disparate domains.

More work is required to understand why certain communication styles are associated with performance at different levels of expertise and whether those relationships are task-specific. I can draw many inferences based on existing theory in the literature pointing to increased awareness and reduced error, but even causation is not ascertainable with these methods. These methods are, however, useful for discovering such areas worthy of further examination.

The generalizable teams research that I argue for in this dissertation is only testable through a combination of studies. Work collecting and analyzing rich qualitative data is needed to better understand why these teams use specific communication styles. Crucially, though, studies using methods similar to those presented in this chapter focusing on teams in disparate domains that share characteristics and pressures like those described in chapter 5 are needed to identify consistencies and differences between team communication practices in teams that might learn from one another. If the kinds of communication associated with performance are consistent between these teams across domains, work to understand team development through learning and training team communication will be vital. Testing different team development strategies in esports allows much wider margins for error and for creative approaches than does testing team development strategies in emergency medicine, for example. Suites of studies testing for similar communication practices across domains will be the first step toward a domain-general understanding of the role of team communication in team cognition and performance. Studies testing development of those communication practices in one domain and testing transference of those practices to teams in other domains will give that domain-general theory actionable value for teams in the wild.

4.6 Summary

This chapter reports a novel 2x2 factorial design comparing communication frequency, style, and content across two kinds of expertise in LoL: experience with teammates and in-game rank. The methods developed for this work build on team science and peer mentoring literature to offer a potential methodology for team communication research that is generalizable across domains for teams that – as described further in chapter 5 – share certain characteristics and work under similar pressures. The findings indicate that Team Expert teams communicate more, are less motivational and collective, but share more information in a more timely manner than Team Novices. Game Experts only significantly differ from Game Novices by communicating more task-oriented temporal information in a more timely manner. Team Novice/Game Novice teams' performance seems to benefit from increased communication frequency, despite their likelihood of communicating less frequently. On the other hand, these TNGN teams' performance also benefits from more motivational communication, which they are more likely to rely on regardless of communication frequency. These results provide insights into types of communication teams of varying levels of expertise can practice and learn to use in pursuit of performance and team development. Future work will explore these same aspects of team communication in similar teams that work in other domains to test these methods and to explore whether these results are consistent across domains.

Chapter 5

Isomorphic Teams

5.1 Introduction

This work focuses on communication in *League of Legends* (LoL), in particular, because of similarities between competitive LoL teams and literature describing small teams in domains outside of esports, like emergency medicine and air traffic control. If expert LoL communication practices relate to stress responses that do not hinder performance, the content, style, and structure of that communication might also benefit teams in contexts with more severe consequences. If expert LoL communication practices do not relate to consistent performance under pressure, there could be an opportunity to adapt communication practices of other domains to test against existing practices in esports. In other words, this is an approach to esports research that would inform life outside of competitive gaming. As McCarthy argued for “chess as the Drosophila [fruit fly] of artificial intelligence” [83], this work argues for esports as a Drosophila of team research.

Better understanding how cognitive skills like attention management emerge on the team level – as opposed to the individual level – is crucial for designing systems that support the teams that work synchronously under time pressure. Identifying strategies for joint attention in elite esports teams specifically will deepen our understanding of how to design for and train coordination in high performance teams more broadly. In the interest of making this research generalizable from esports teams to other domains, I am considering a variety of teams in other domains as isomorphic to esports teams. The characteristics of interest that make these teams isomorphic include temporal pressure, attentional synchrony, tech-mediated communication, shared access to at least a portion of the task-relevant information, shared goals, differentiated roles, and intentional leadership structure. Well-researched teams that fit this definition of isomorphism include those in emergency management and medicine [101], naval navigation [61], and air traffic control [77] giving credence to the idea that strategies for developing attentional control in esports teams might generalize to less controllable and replicable contexts. If so, studying – even designing controlled experiments around – team level cognitive processes in the context of competitive video games can translate to safer design and more effective learning strategies for these isomorphic teams.

The isomorphic teams described in the introduction were chosen for certain similarities with esports teams so that future work might generalize beyond competitive video game play. The goal in describing these teams is to highlight a category of team that is defined by characteristics as opposed to domain. This allows research that identifies predictors of performance in one such team to enter into the discussion of team performance in other domains with isomorphic teams.

5.2 Characteristics of Esports and Isomorphic Teams

Table 5.1 uses examples from teamwork in League of Legends (LoL) [42] and three non-esports contexts to illustrate how the characteristics that define this category manifest across domains. The argument presented with this table is that there is a category of team whose members work under temporal pressure, require attentional synchrony to accomplish tasks, require some communication through technology as opposed to face to face, have common access to at least some task-relevant information, share common goals, work in clearly differentiated roles, and employ an intentional leadership structure. This definition intentionally omits any reference to the content of the teams' goals and tasks. The strength of this definition is that omission, since it allows comparisons of teams that work with similar structures and under similar pressures but may not work in similar domains.

LoL teams, for example, must perform under time pressure both because they are racing to destroy their opponent's base before their opponent destroys theirs and because success in teamfights depends on split-second coordination of multiple players using specific abilities to engage or disengage enemy players. That level of coordination in teamfights also requires attentional synchrony. In order to understand when and how they need to act to land combinations of attacks with their teammates, each player attends to the same stimuli. An example is Blitzcrank's hook ability. If Blitzcrank hits an enemy with its hook, the target is pulled toward Blitzcrank, where they are vulnerable to further attacks. Every time Blitzcrank uses its hook, though, it cannot be used for a few seconds [1]. When deciding if and when to engage against a team with a Blitzcrank, success against a skilled opponent requires each player attend to that hook simultaneously. The team's best chance of winning the fight is immediately after hook is used, because they have at least 8.8 seconds where they can engage without the threat of being pulled toward Blitzcrank. If some team members are not attending to the hook, valuable time is wasted alerting them that Blitzcrank just used it. Instead of immediately attacking, the team either waits and the opportunity is lost, or some members attack and some do not, splitting the team and leaving them vulnerable. Blitzcrank's hook is just one example of an ability that has to be played around in order to

[1] Base cooldown of 20 seconds at match start. By mid- to late-game, when teamfights are more common, it can have a base cooldown of 16 seconds minus 40% to 45% maximum cooldown reduction from items, leaving a minimum of 8.8 seconds between casts. This is considered a long cooldown for an ability, generally only surpassed by ultimate abilities and summoner spells.

win teamfights. In any given game, each team has a number of such tools to work with and against. Communication about teamfight strategy must therefore happen in large part before it is actually time to fight, because once a fight begins, communication is often reduced to single-word or ping commands to announce targets or moments to act. Without each player attending to the same stimuli, those commands lose context and acting upon them at the right time in the right manner is not consistently feasible.

Emergency department staff do not have a competitor. Their goals have nothing to do with out-smarting or out-coordinating another team. The tasks they complete to achieve their goals look very different from fighting in competitive video games, changing the flap orientation of airplane wings, or swapping tires on a Formula 1 car. The structures and pressures within which they work, however, are similar enough to a Formula 1 pit-stop and an aircraft landing procedure for Catchpole et al. [13] to design a new patient handover protocol based on observations of pit-stops and interviews with a race director and two aircraft captains. The new protocol reduced errors in task completion and omissions of information transferred during patient handover from the operating theater to the intensive care unit (ICU), in addition to shortening the duration of that process. From those observations and interviews, the researchers made changes to the leadership structure, temporal ordering of tasks, task allocation, safety checks, and communication structure of the teams of doctors and nurses that handle the transfer of a patient from surgery to ICU. Each of these changes made part of the process more explicitly structured. For instance, based on the clear responsibility and leadership of the lollipop man's role in a pit-stop and the captain's role on a flight, the new protocol gave clear "overall responsibility for coordinating the team" to the anesthetist for the duration of the handover and to the intensivist at the end of the handover, where previously it was "unclear who was in charge" at any given moment [13]. Similarly, the expectations of the structure of communication were made explicit based on the "very little verbal communication during a pit-stop" and the "explicit communication strategies used to ensure a calm and organized atmosphere" [13] in an aircraft. During patient handover, the researchers limited speaking to the anesthetist and surgeon before allowing general discussion, instead of the “several simultaneous discussions” that occurred under the old, less explicitly structured, handover protocol. To evaluate the old and new protocols, a researcher observed 23 old protocol handovers and 27 new protocol handovers. Errors in the procedure were recorded using a checklist of tasks that comprise a handover; omissions in transferring information were recorded using a checklist of key pieces of information that should always be shared during handover; the time “from the moment the patient entered the ICU to the moment the theater team left the bedside” was recorded; and team performance was rated by the observer in terms of “leadership and teamwork, task management, workspace and equipment, [and] situation awareness” on a five-point Likert scale for each construct [13]. Every measure showed statistically significant improvement under the new protocol developed by adapting successful practices used by isomorphic teams.

Among emergency department staff in hospitals, temporal pressure is the result of emergency rooms full of sick and injured patients waiting to be cared for and, in some cases, government mandates of the maximum amount of time a hospital is permitted before tending to a new patient waiting in the emergency room [37]. For Formula 1 pit crews it comes from their team’s foremost goal: be faster than everyone else without making errors. In a cockpit, temporal pressure arises from the need to decide how to alter flight to reach a safe speed, heading, and altitude for landing [61]. Catchpole et al.’s [13] results show promise that teams can learn from the practices of isomorphic teams despite working in disparate domains. The goal of establishing this category of isomorphic teams around characteristics found in esports teams is to allow lessons learned from researching esports teams to be useful in other contexts where data are harder to collect.

Note that table 5.1 is not itself a taxonomy. Rather it outlines one category of isomorphic teams that would be described within a taxonomy. While that taxonomy will be helpful for understanding the range of teams across domains that might learn from each other, detailing this one category is enough to begin work that might generalize between esports and isomorphic teams.

Table 5.1: Characteristics and examples from *League of Legends* and isomorphic teams.

Feature	*Esports (LoL)*	*Emergency medicine*	*Aircraft navigation*	*Formula 1*
Temporal pressure	Split-second coordination [96]	”The four-hour target” [37] ”The handover of patients from theater to ICU...” [13]	Precise timing of changes in elevation, heading, and speed to stay safe and on schedule [61]	”The pit-stop... (change four tyres and fill with fuel) under huge time pressure (approx 7s) with minimal error” [13]
Attentional synchrony	Target acquisition in teamfights Minion wave management	Clinicians look at patient records together when problem-solving [4]	Pilots’ and copilots’ ”redundancy in the visual field” [38] ”Crew coordination cross-checking procedures” [61]	Sensor data and warnings displayed simultaneously to driver, technical team, and race engineer
Common access to information	On all team members’ screens: - Minimap - Teammate health and mana - Teammate and enemy items - Text chat log	”Shared knowledge of task structure and team processes” [101]	Pilots and copilots have identical sets of gauges, and checklist procedure sometimes necessitate joint attention to a specific gauge [61]	Sensor data avilable to driver, race engineer, and technical team

Table 5.1 (*continued*): Characteristics and examples from *League of Legends* and isomorphic teams.

Feature	*Esports (LoL)*	*Emergency medicine*	*Aircraft navigation*	*Formula 1*
Common goals	Destroy enemy nexus - Destroy towers - Control objectives - Control vision - Amass gold and experience	”Well-articulated and understood goals and vision are necessary for giving ... as well as integrating feedback...” [101]	Navigate safely and efficiently from origin to destination Complete checklist procedure accurately	Win race - Complete laps and pit stops faster than opponents - Execute race strategy
Differentiated roles	Map positions (e.g. top laner, jungler) Teamfight roles (e.g. tank, engage)	”Allows teams member to formulate accurate expectations of ... needs during high-stress work episodes.” [101]	”Explicit acknowledged allocation of tasks for emergencies” [13]	”Each team member has only one or two clearly defined tasks.” [13]
Intentional leadership structure	Shotcaller	Resuscitation team leaders [19]	Captain [13]	- Race team: race engineer - Technical team: chief technical officer - Pit crew: lollipop man [13]

5.3 Empirical Work toward Generalization

Taken together with the methods and findings reported in chapter 4, this category of team – and this way of thinking about teams in disparate domains – is an invitation for future work toward domain-general team science. Building an understanding of how these teams compare in terms of the aspects of communication detailed in chapter 4 is a starting point for developing a kind of research that might allow, for example, a team in emergency medicine to improve their patient care based on knowledge gained from people playing video games.

Chapter 6

Conclusion

This dissertation begins with a description of how I arrived at studying teams of people playing video games. Through these chapters I explain my focus on team cognition and communication, identifying video games as a context for studying phenomena that can provide insights for higher consequence domains. I review previous literature and ongoing academic conversations about team cognition, team taxonomies, and esports, highlighting the issues with many theoretically-derived taxonomies not building on empirical data. The methods for the novel study presented in chapter 4 are described and scoped to establish and justify work toward domain-general teams research that can, with future work, allow findings from teams in one context to reliably inform the practices of teams with similar characteristics and under similar pressures in seemingly disparate domains. This study uses those methods to better understand what differentiates the communication of expert and novice teams in terms of both experience working as a team and game-specific expertise. The scope of this work is both narrow – in that it focuses on communication in teams that play a particular esport at certain levels of expertise – and broad – in that it is designed to explore how teams communicate to perform under pressure, regardless of domain. The findings advance understanding of how these teams communicate when tight coordination and performance matter most, and how that communication differs in expert and novice teams. The methods developed for this dissertation offer a means for broadening that knowledge across contexts.

A near constant connection through networked computing permeates how we work and how we play. How we coordinate and collaborate often dictates how we feel, how we learn, and how we perform. Communication is how we develop and execute that teamwork. I pursue generalizability in describing and improving team communication so that advances in the practices of teams in low consequence domains can inform the practices of teams that operate under similar pressures but with much higher consequences to their work. This dissertation is far from achieving that goal, but it presents the argument, details my approach, and expounds research toward a domain-general understanding of team communication.

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Appendix A

League of Legends Map

Figure A.1: The *League of Legends* map [43].

Appendix B

Recruitment Flyer

Research Participants Needed

Measuring Performance and Communication of Esports Players

Lead Researcher Dr. Constance Steinkuehler and researchers from the Informatics Department at the University of California, Irvine are recruiting participants for a study of in-game data collection while playing League of Legends. This study aims to explore the in-game behavior of esports players.

Who is eligible to participate?
- At least 18 years of age or older & a student of UC-Wide campuses.
- League of Legends players whose rank is Bronze and higher.
- You are encouraged to participate as a team of 5 people if you have a group of friends or teammates that plays together regularly (Your team must have played at least 10 games together).
- You can still participate as a solo player.
- You must have a webcam or a smartphone to join a video chat during the session

When and Where?
- The session will consist of 3 Summoner's Rift matches and pre/post survey and interview.
- Scheduling will be discussed with participants through email.
- Study will be conducted at your own place.
- We will send a heart rate tracker and instruction before the study

What do I do?
- You will be asked to play 3 matches of League of Legends with other participants. Who is on which team will be decided by the researchers beforehand. Due to the restriction regarding to COVID-19, you will be guided to participate in the study remotely.
    - During play, in-game events, keypresses, and mouse movements will be collected
    - Summative statistics of your play will be collected through the Riot Games' API
    - Your screen and facial expressions will be video-recorded
    - Your heart rate will be logged through a wearable device. Any identifiable data such as your summoner name and facial image will be de-identified when stored.
- You will be given a pretest survey (2-5 minutes) before starting the session. Immediately following the series of 3 matches, you will be asked to complete a posttest survey (10 minutes) and will be asked to participate in a focus group/individual interview (30 minutes)

Compensation
- The wearable device (worth $69.99) used for the study plus $20 Amazon gift card upon completion of a full session.
- Extra $25 Amazon gift card when participating as a team of 5 players

How to participate
If you are interested in participating in this study, please contact Jeseok Lee at jesl@uci.edu or Jason Reitman at jreitman@uci.edu

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Figure B.1: Recruitment flyer for adult participants.

Appendix C

Demographic Survey Items

The items on the pre-session survey, presented below as they were presented to the participants through Qualtrics, were all free response.

- Summoner Name:
- Year of birth:
- Gender:
- Current League of Legends rank:
- Highest achieved League of Legends rank:
- Number of games of League of Legends I have played with my teammates (can be an estimate):

Appendix D

Example Period of Interest Coding

Table D.1: Example PoI from game 3 of TNGN session 2

ToT	Moti	Info	Time	Coll	Temp
Lets take the dragon-	0	+	+	-	-
No not in time I don't think	0	+	+	+	-
Yeah not in time, Okay	0	+	+	0	-
Ah damn	-	-	-	0	-
Well she's not here, ya know	0	+	+	-	-
This is a 5v4 this is really good	+	+	+	+	-
Just ward	0	+	+	0	-
Can we just drag this out and then just take it?	0	+	+	+	-
They're all here so if we can drag it out, trust	0	+	+	+	-
OHH This is bad	-	-	+	0	-
She's here she's here	0	+	+	-	-
Oh god	-	-	-	0	-
I'm leaving	0	+	+	-	-
She's half	0	+	+	-	-
She doesn't die though she just doesn't die	0	+	+	-	-
That's tough	-	-	-	0	-
But we got the drag	0	+	-	+	-
Did we?	0	+	-	+	-
No I don't think so	0	+	-	-	-
We did not	0	+	-	+	-
Yeah I'll be honest focusing (them) and then it was their dragon, my fault	0	+	-	-	-
No worries	0	-	-	0	-
All good	+	-	-	0	-
Ah shit	-	-	-	0	-
Morgana does a lot	0	+	+	-	-
Her ult set up the Irelia	0	+	-	-	-
Oh god no	-	-	-	0	-
That's tough	-	-	-	0	-
Ah fuck	-	-	-	0	-
She just runs in, it's hard to run away	0	+	+	-	-
Do we even get up in time?	0	+	+	+	+
Close game	0	-	+	0	-
Is that game?	0	+	+	0	-
Yeah I think that's game	0	+	+	-	-
I think so I'll be honest	0	+	+	-	-
Pretty close	0	+	+	0	-
I think that's open inhib, open nexus sorry	-	+	+	-	-
Yeah that's it	0	+	+	0	-

Appendix E

Visualizations of Communication Styles by Group

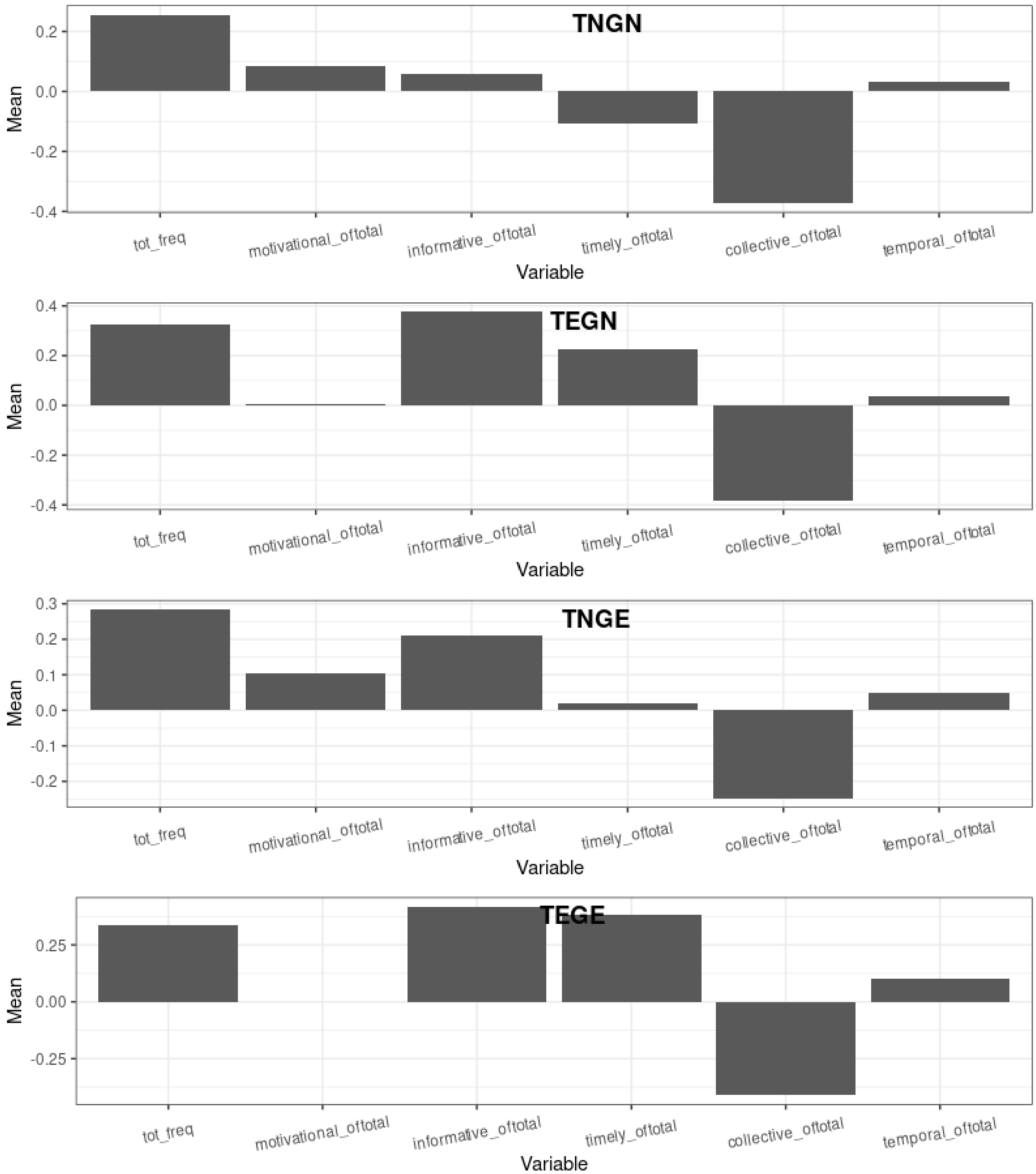

Figure E.1: Bar graphs of communication frequency and quality proportions in each group.

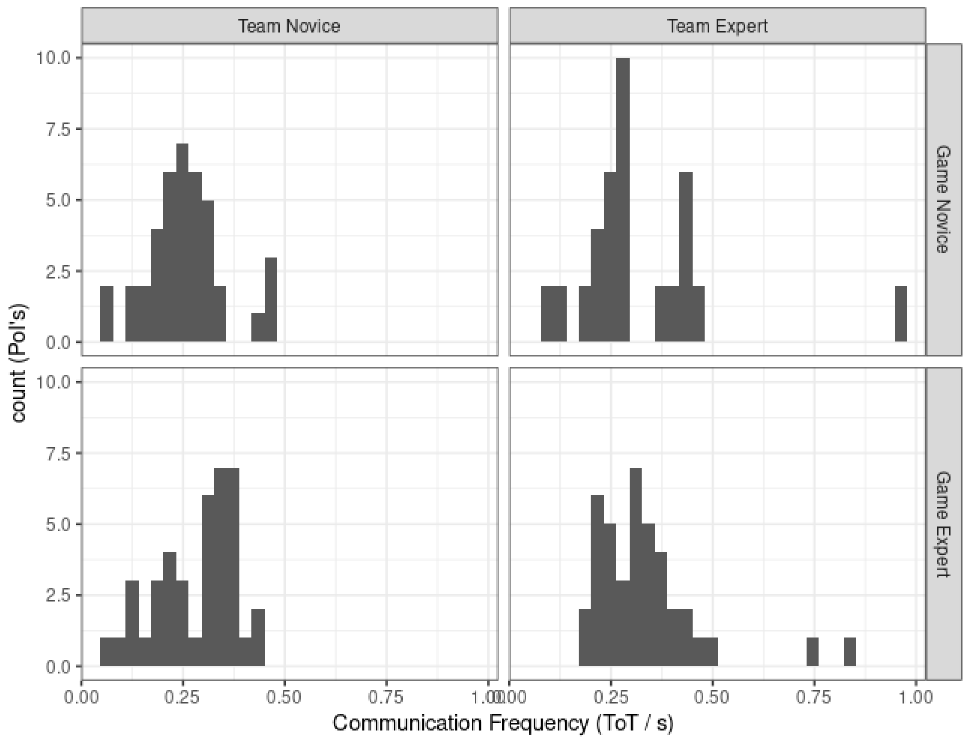

Figure E.2: Histogram of communication frequency in each group.

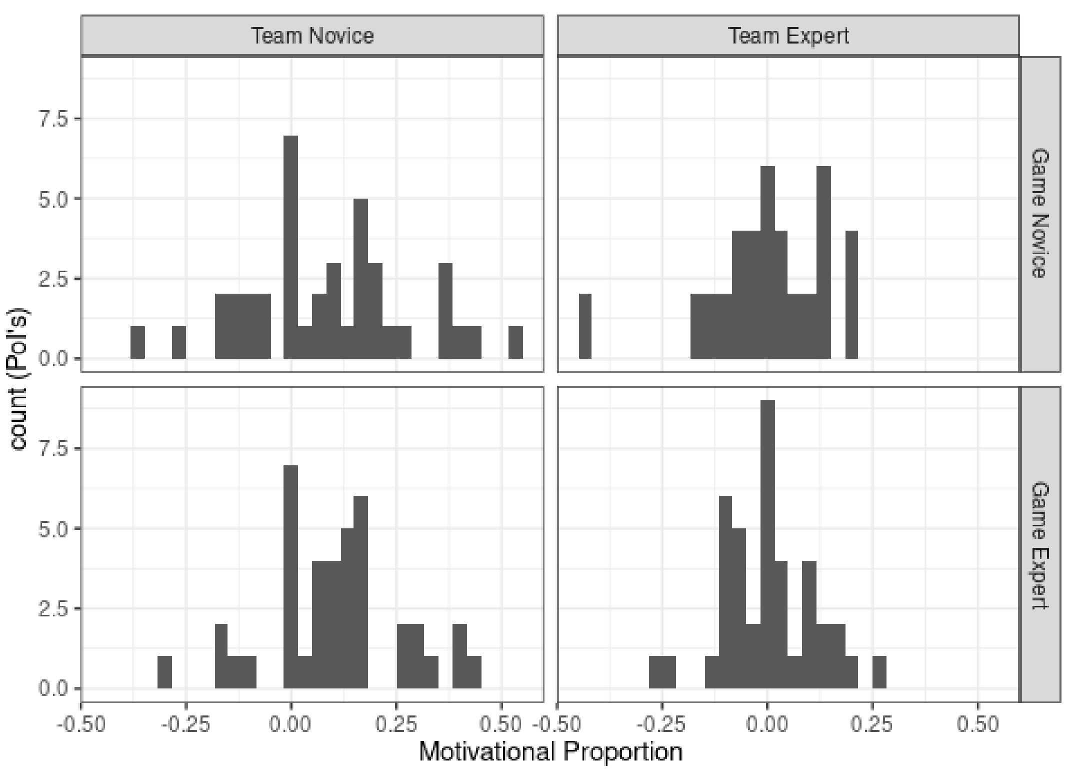

Figure E.3: Histogram of motivational proportion in each group.

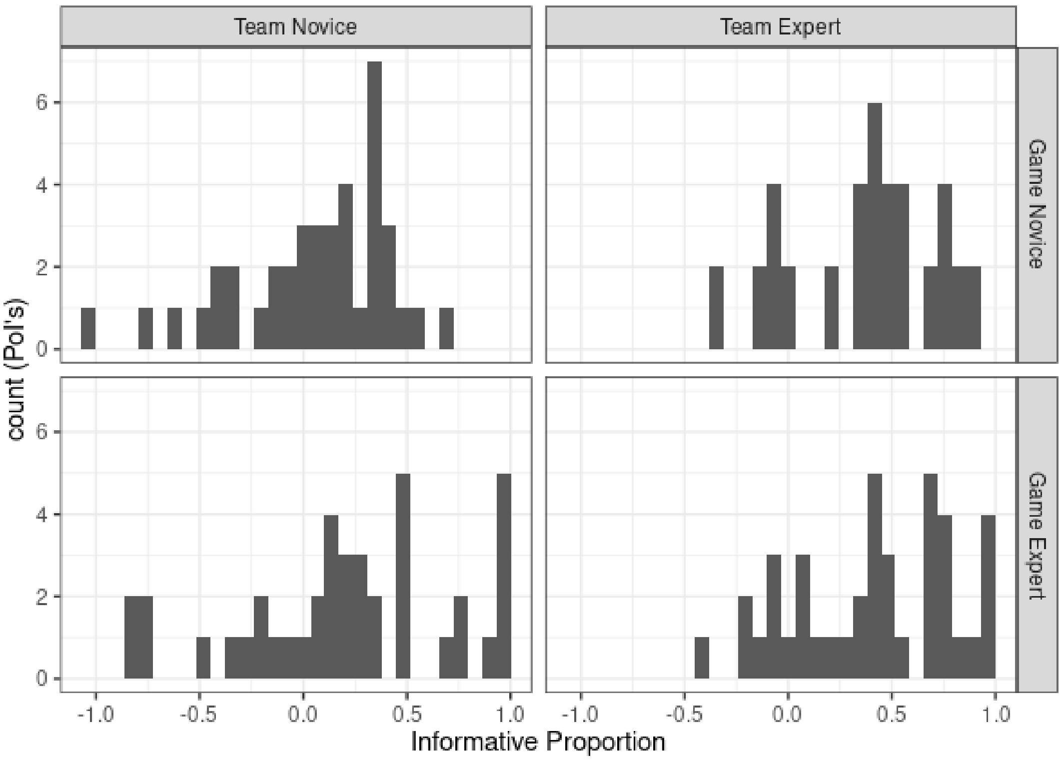

Figure E.4: Histogram of informative proportion in each group.

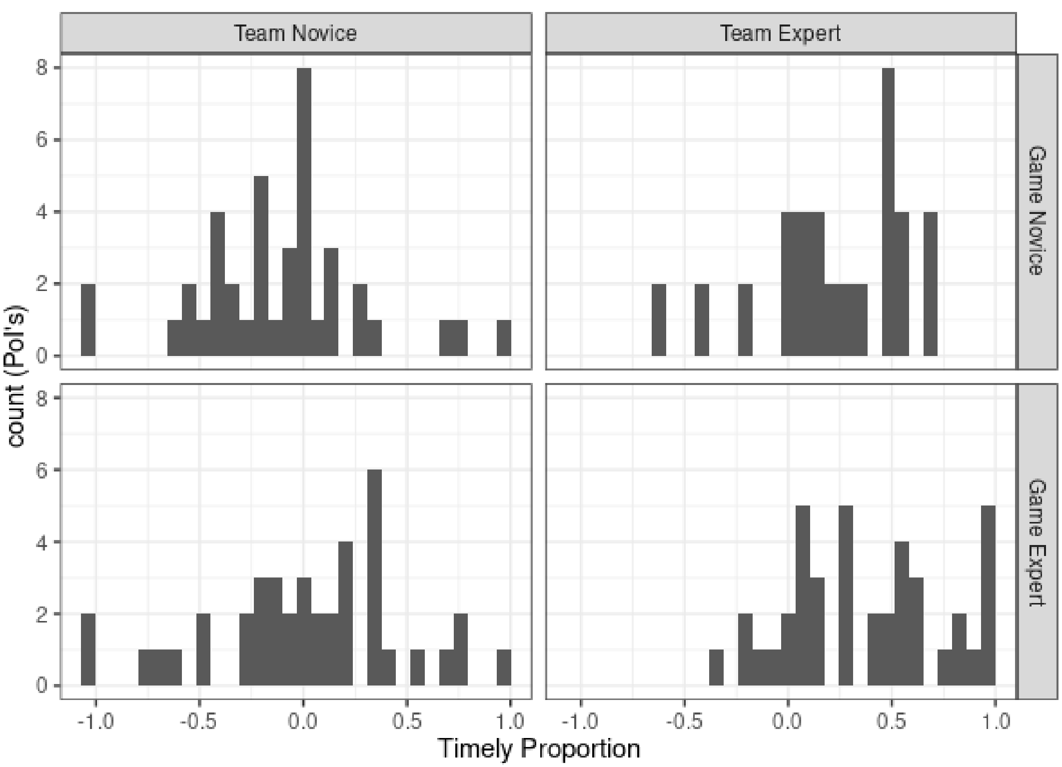

Figure E.5: Histogram of timely proportion in each group.

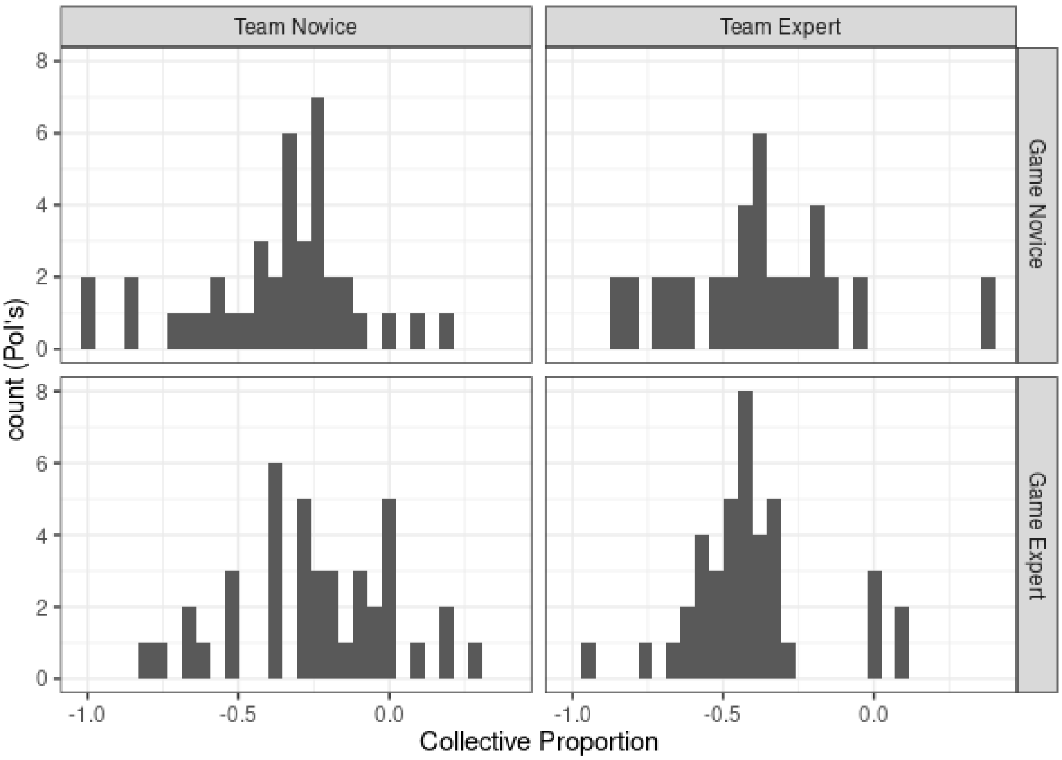

Figure E.6: Histogram of collective proportion in each group.

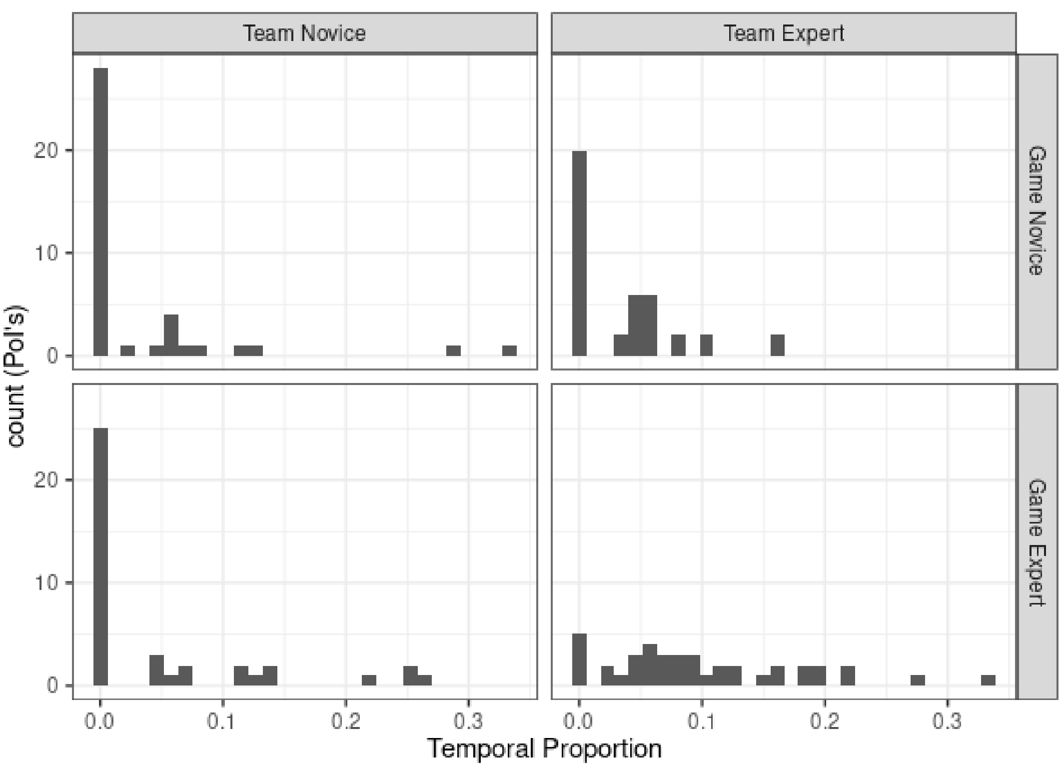

Figure E.7: Histogram of temporal information proportion in each group.

Appendix F

Visualizations of Relationships between Communication Styles and Performance

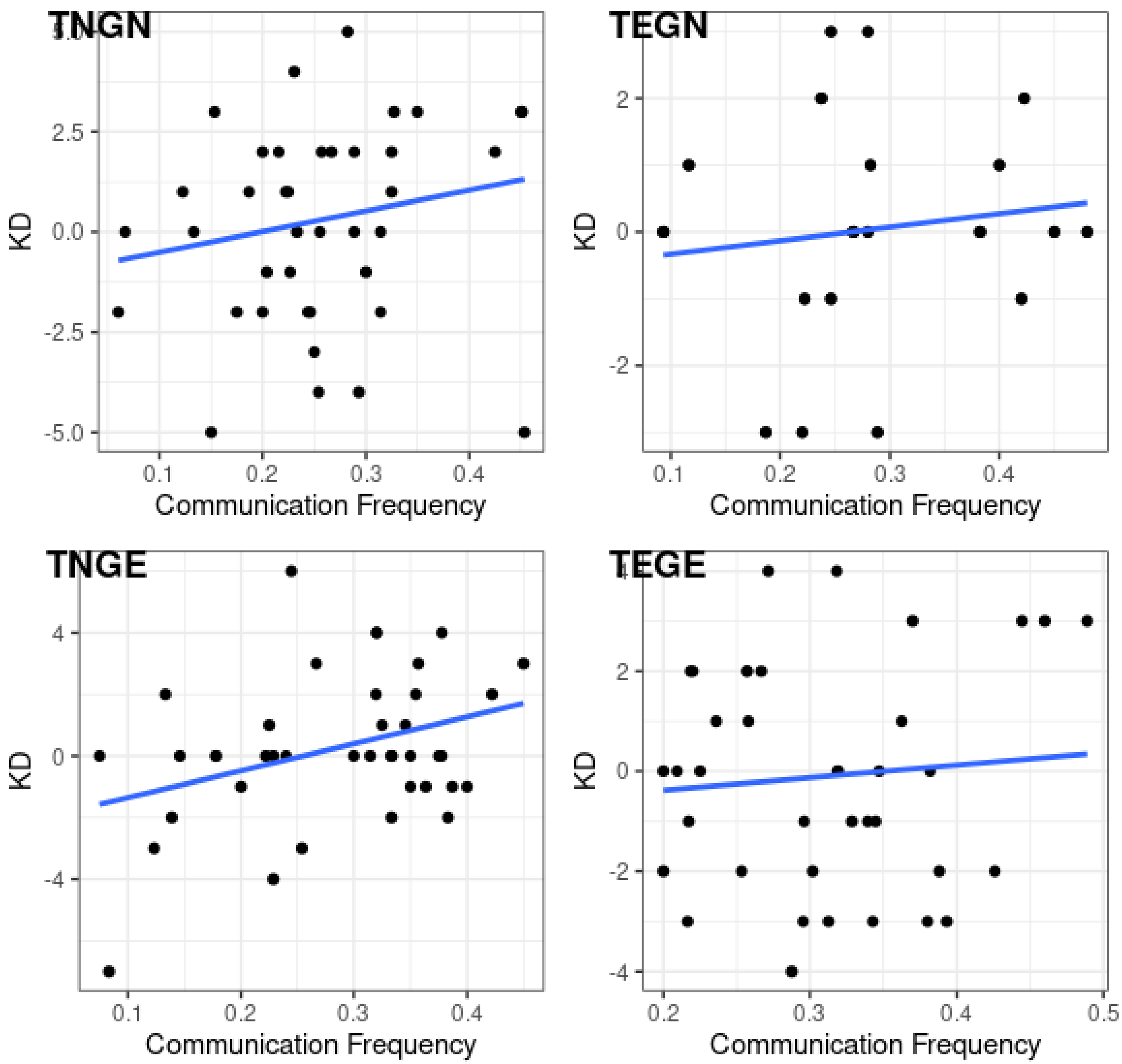

Figure F.1: Scatter plot of KD performance by communication frequency in each group.

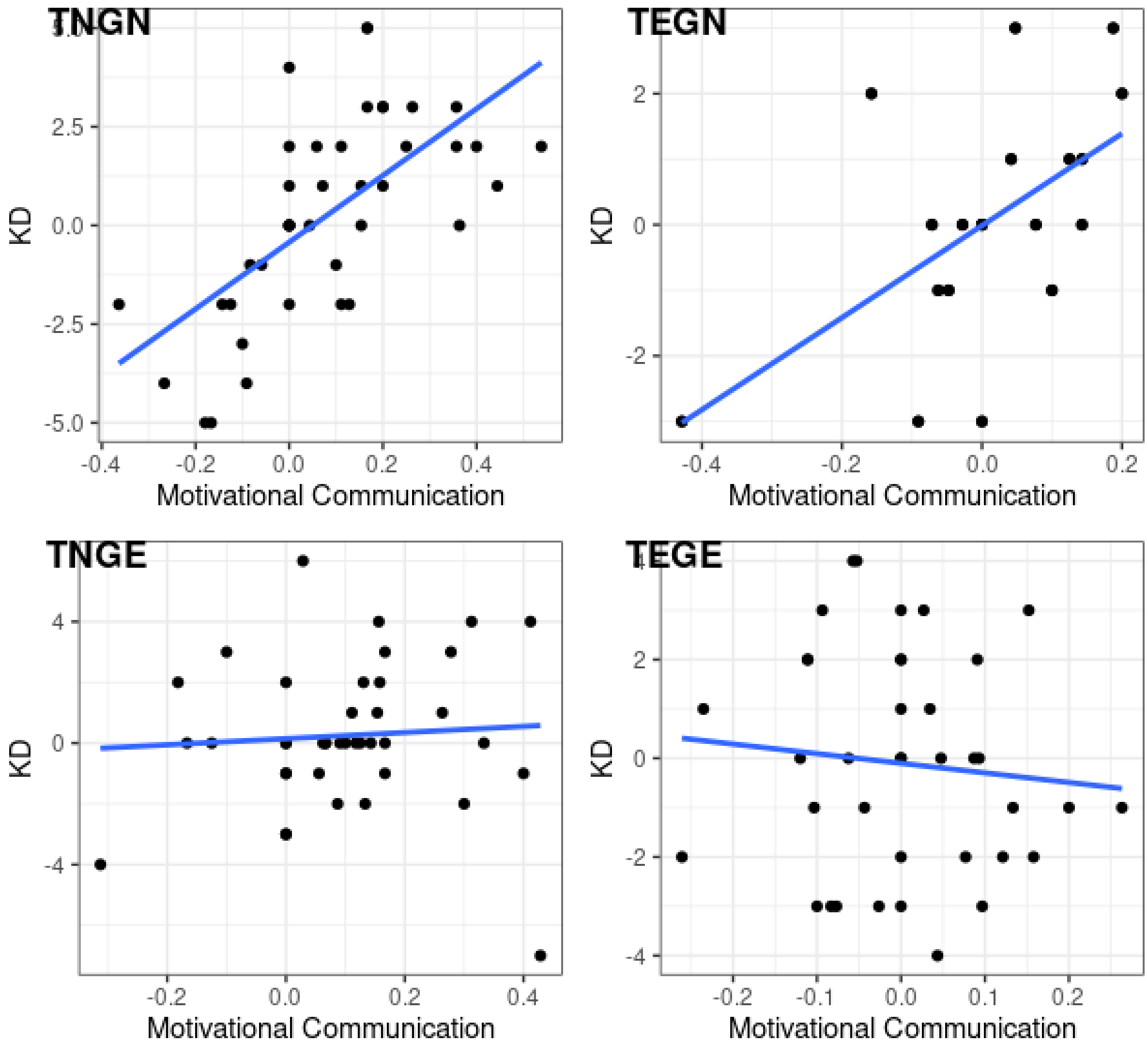

Figure F.2: Scatter plot of KD performance by motivational communication in each group.

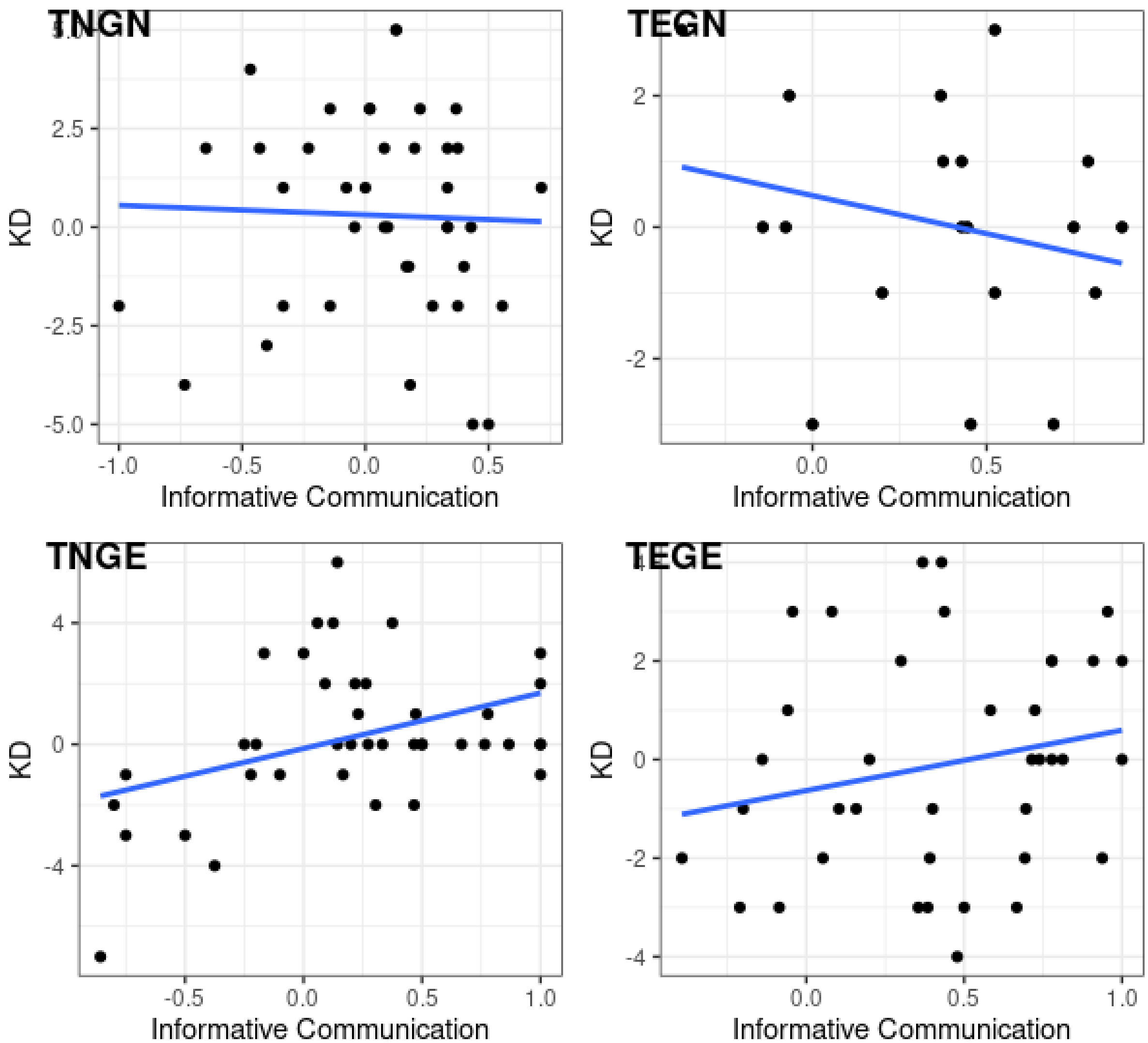

Figure F.3: Scatter plot of KD performance by informative communication in each group.

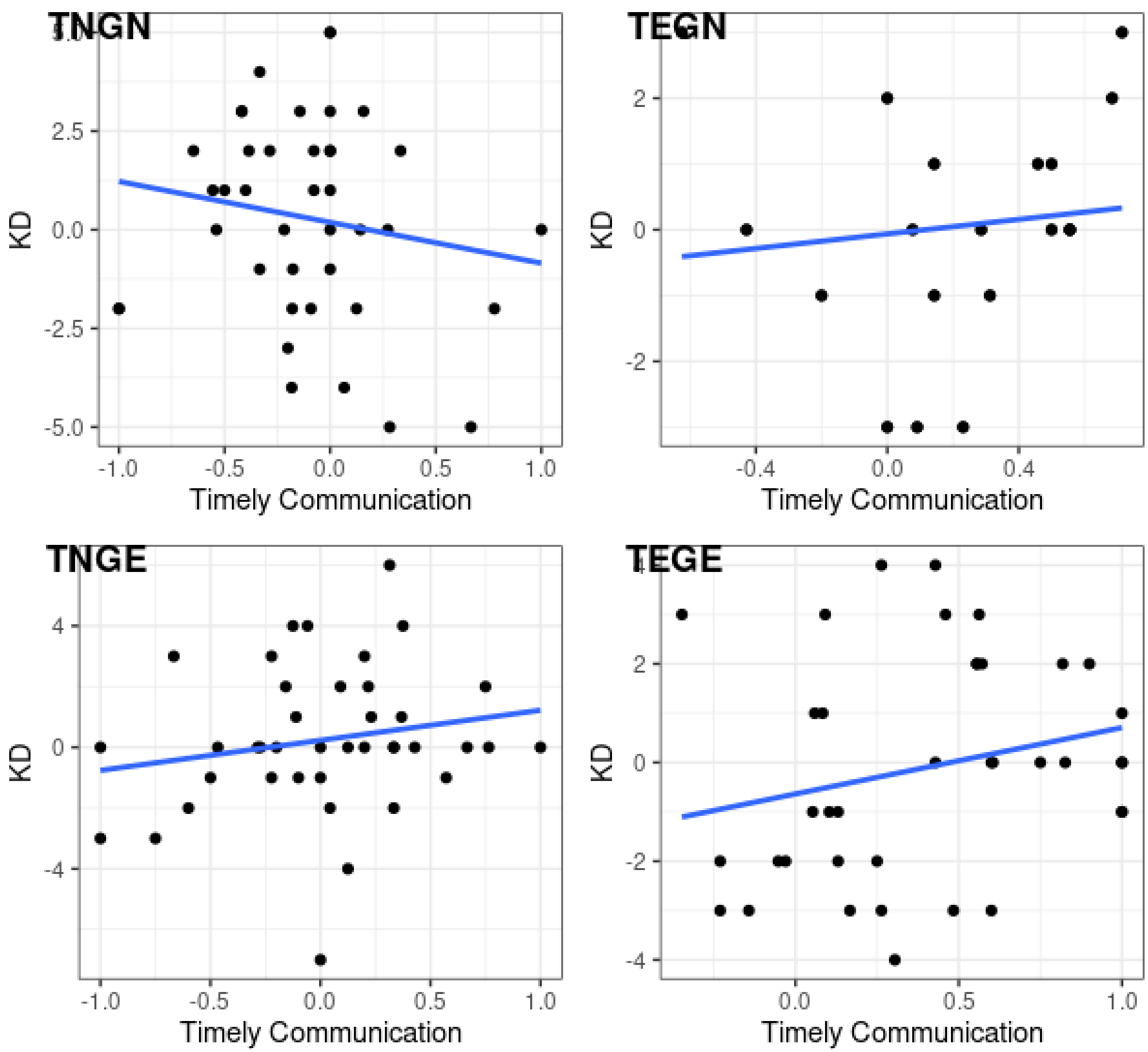

Figure F.4: Scatter plot of KD performance by timely communication in each group.

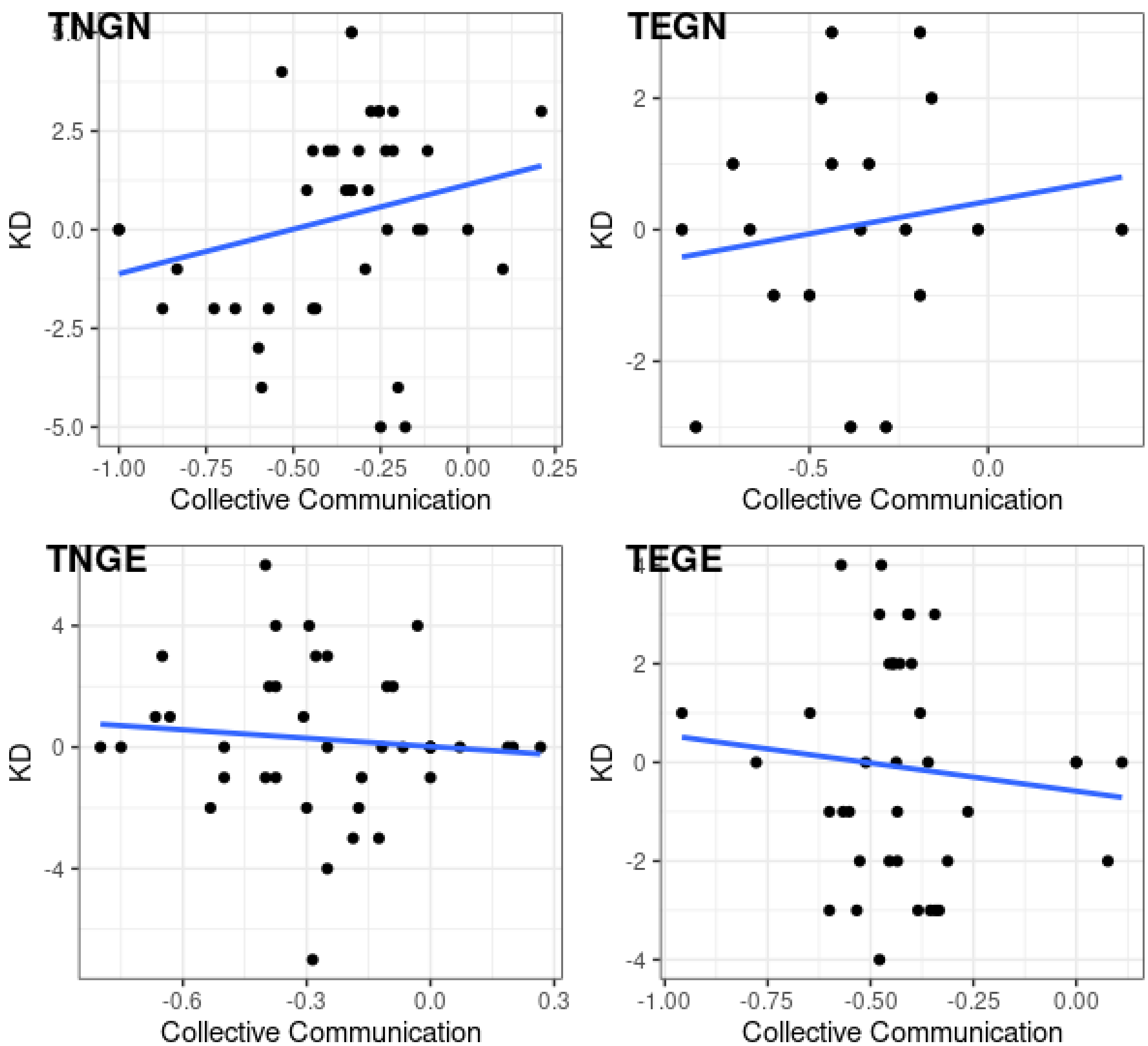

Figure F.5: Scatter plot of KD performance by collective communication in each group.

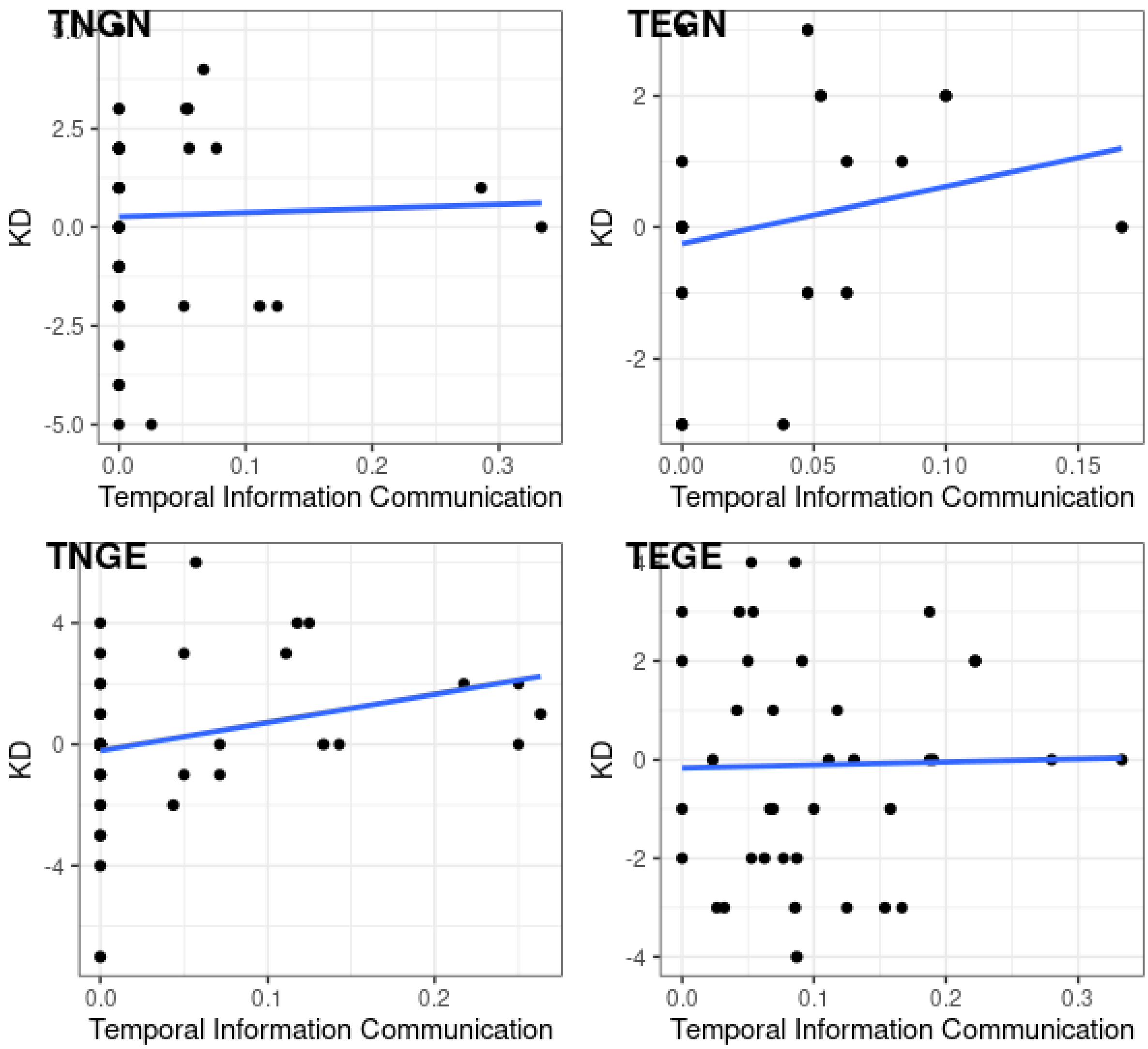

Figure F.6: Scatter plot of KD performance by temporal information communicated in each group.

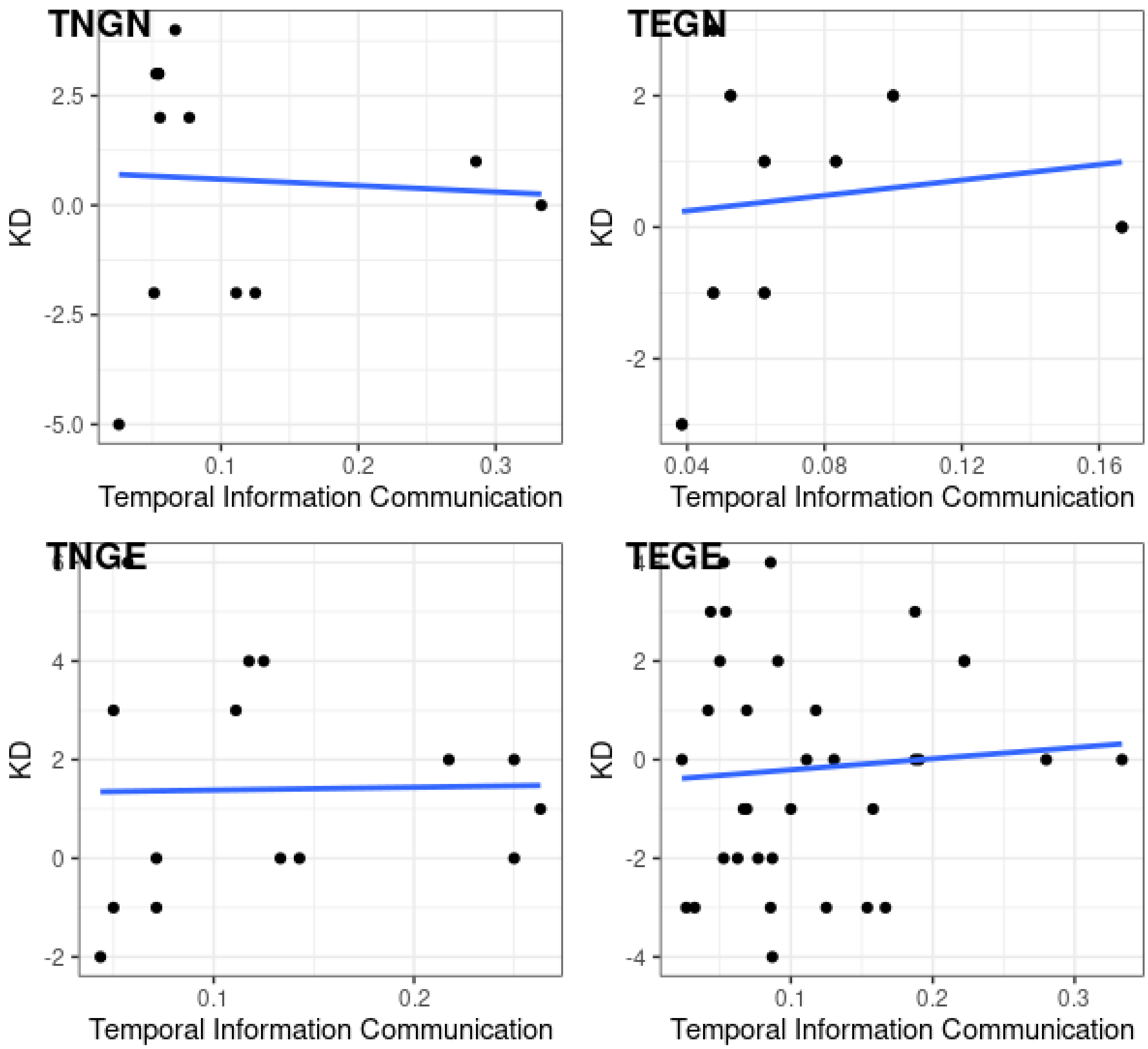

Figure F.7: Scatter plot of KD performance by temporal information communicated in each group, omitting periods with no temporal information communicated.

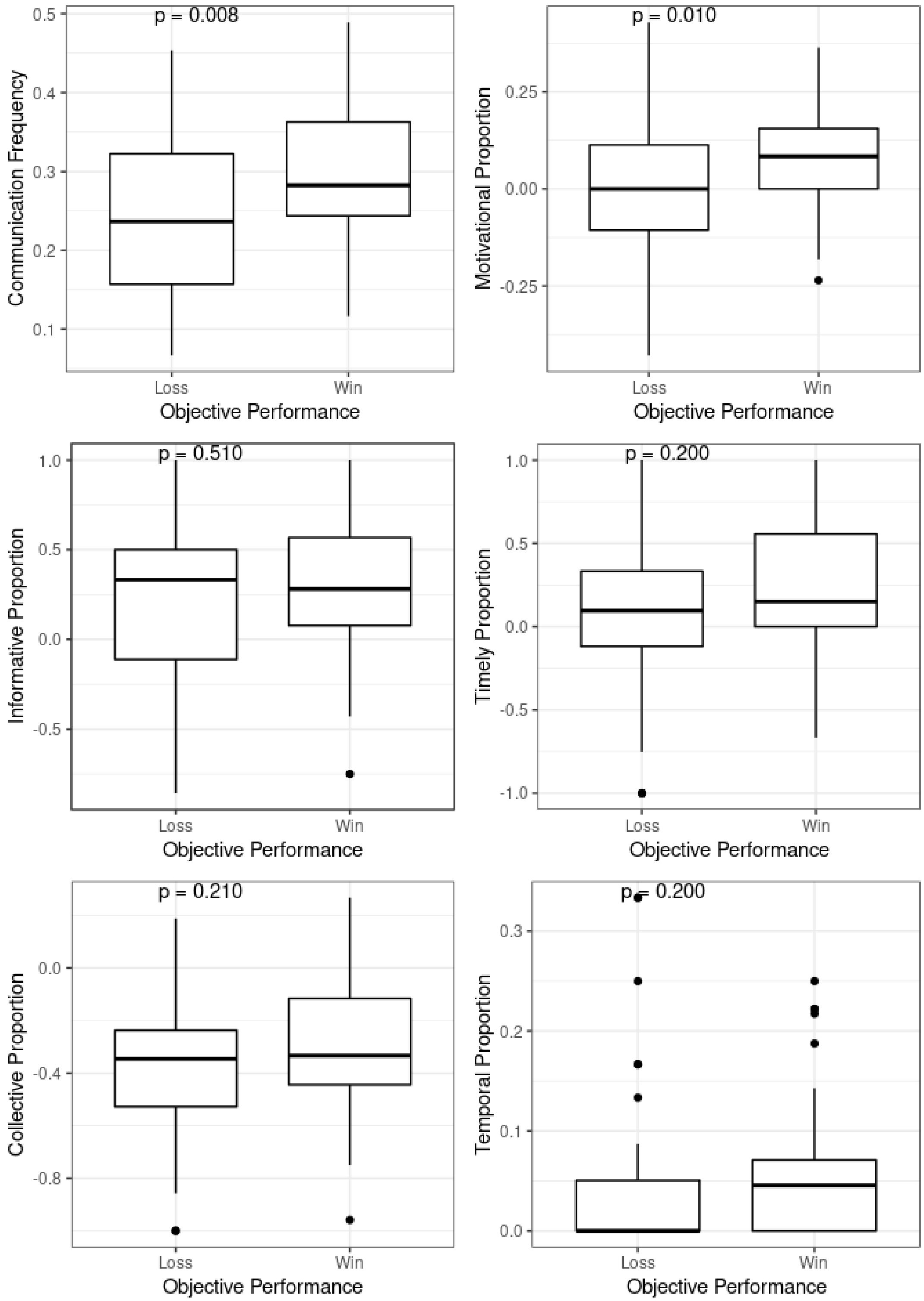

Figure F.8: Boxplots of communication frequency and qualities by objective performance over the entire corpus.

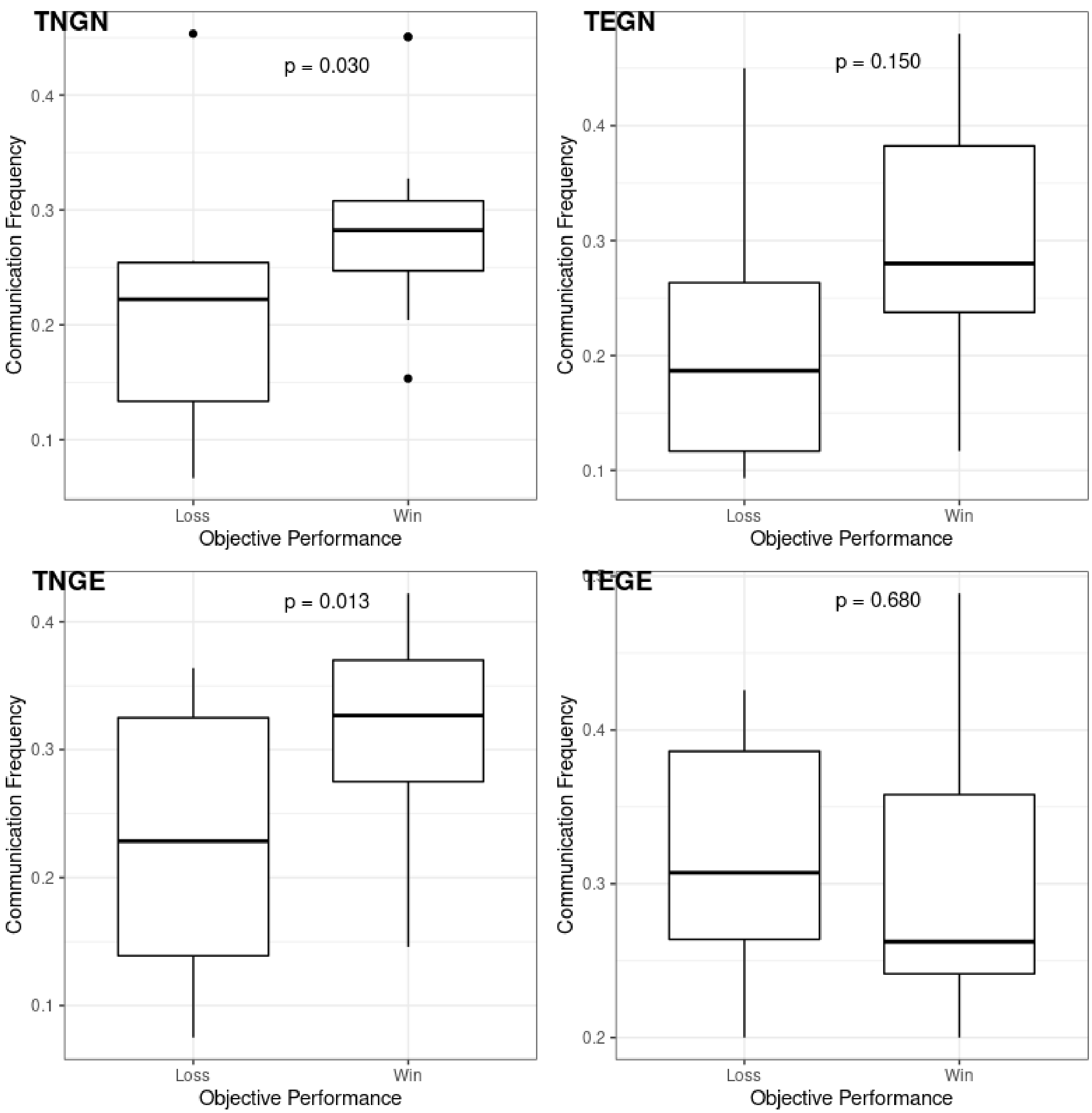

Figure F.9: Boxplots of communication frequency by objective performance in each group.

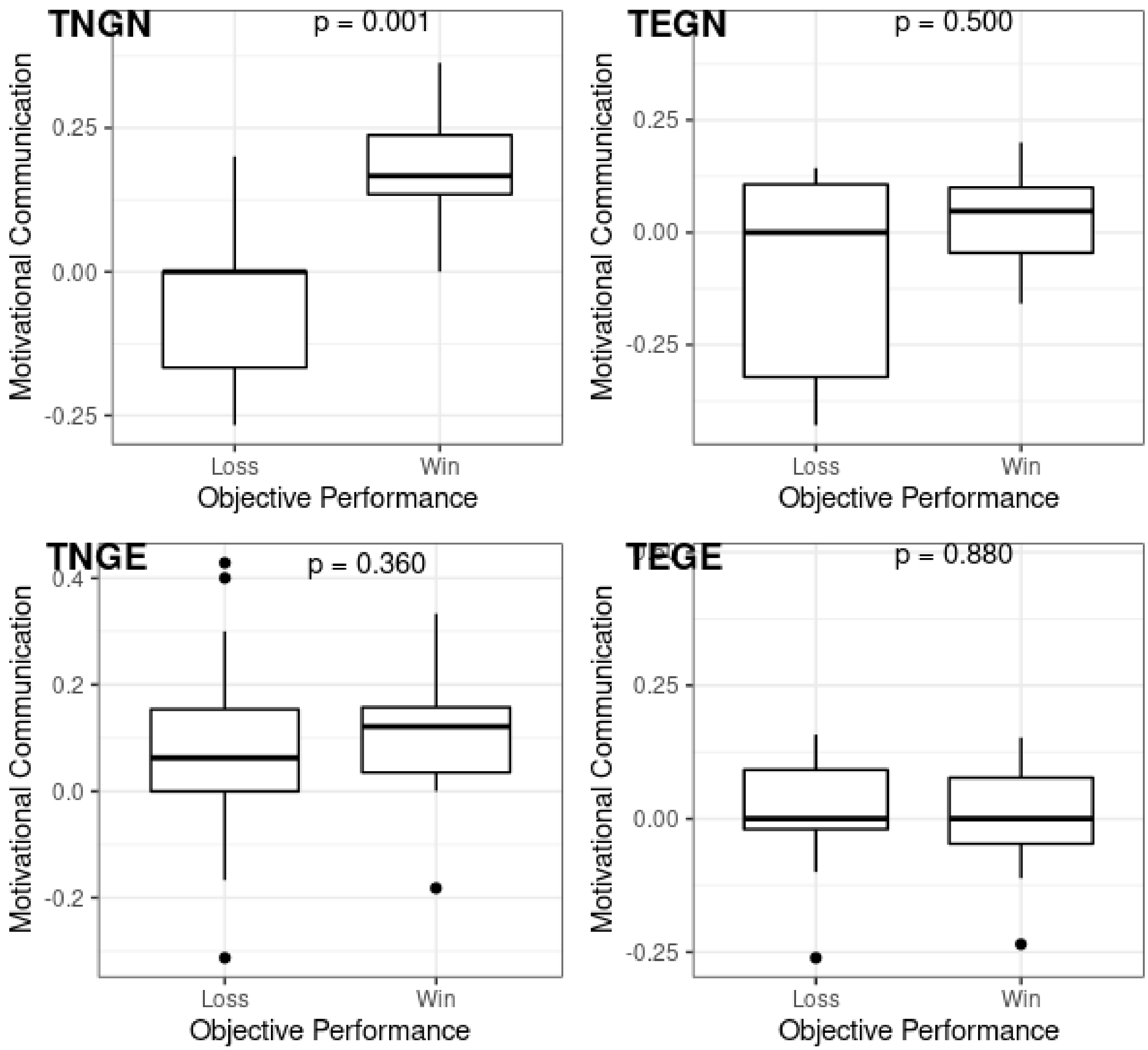

Figure F.10: Boxplots of motivational communication by objective performance in each group.

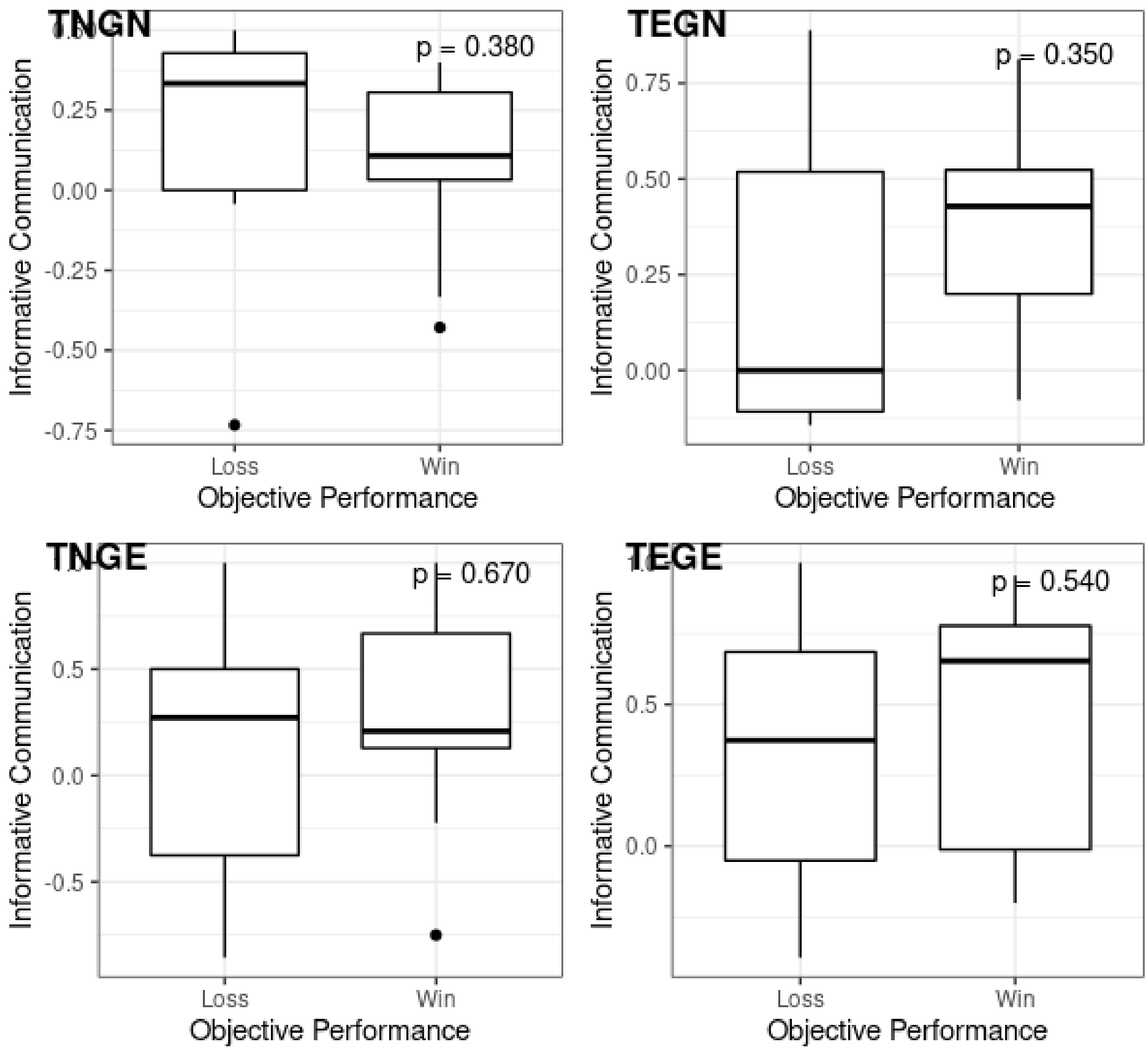

Figure F.11: Boxplots of informative communication by objective performance in each group.

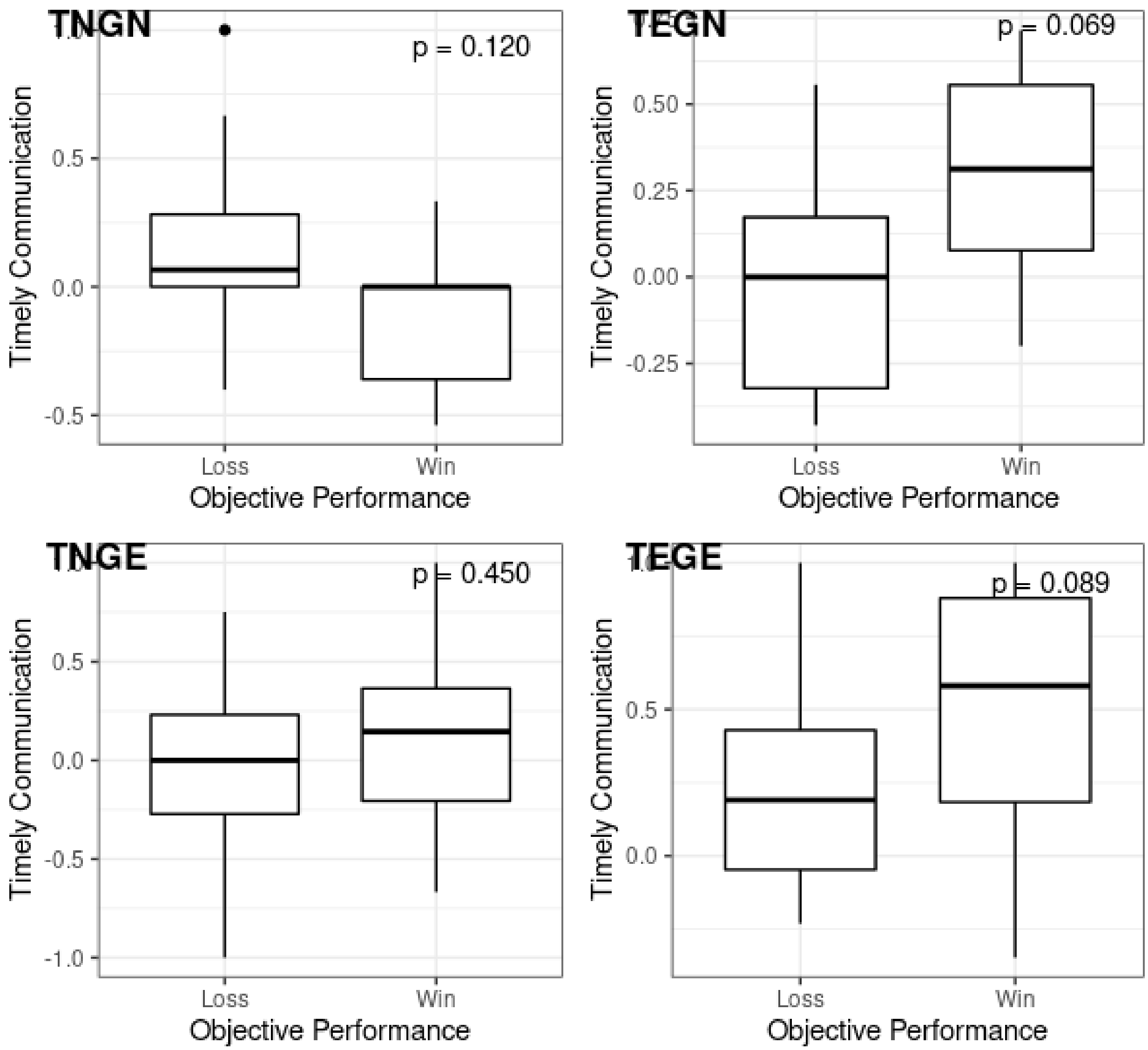

Figure F.12: Boxplots of timely communication by objective performance in each group.

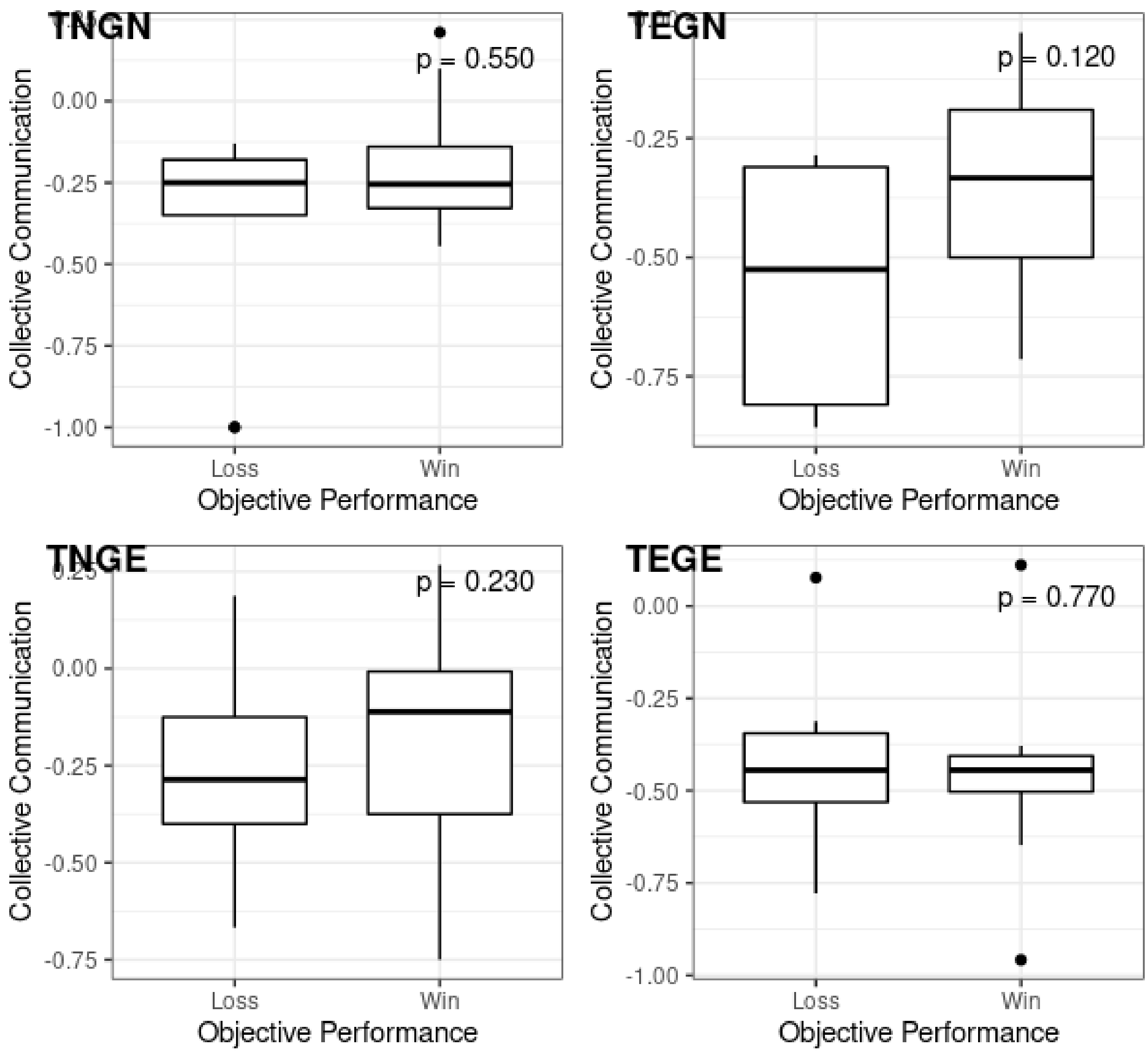

Figure F.13: Boxplots of collective communication by objective performance in each group.

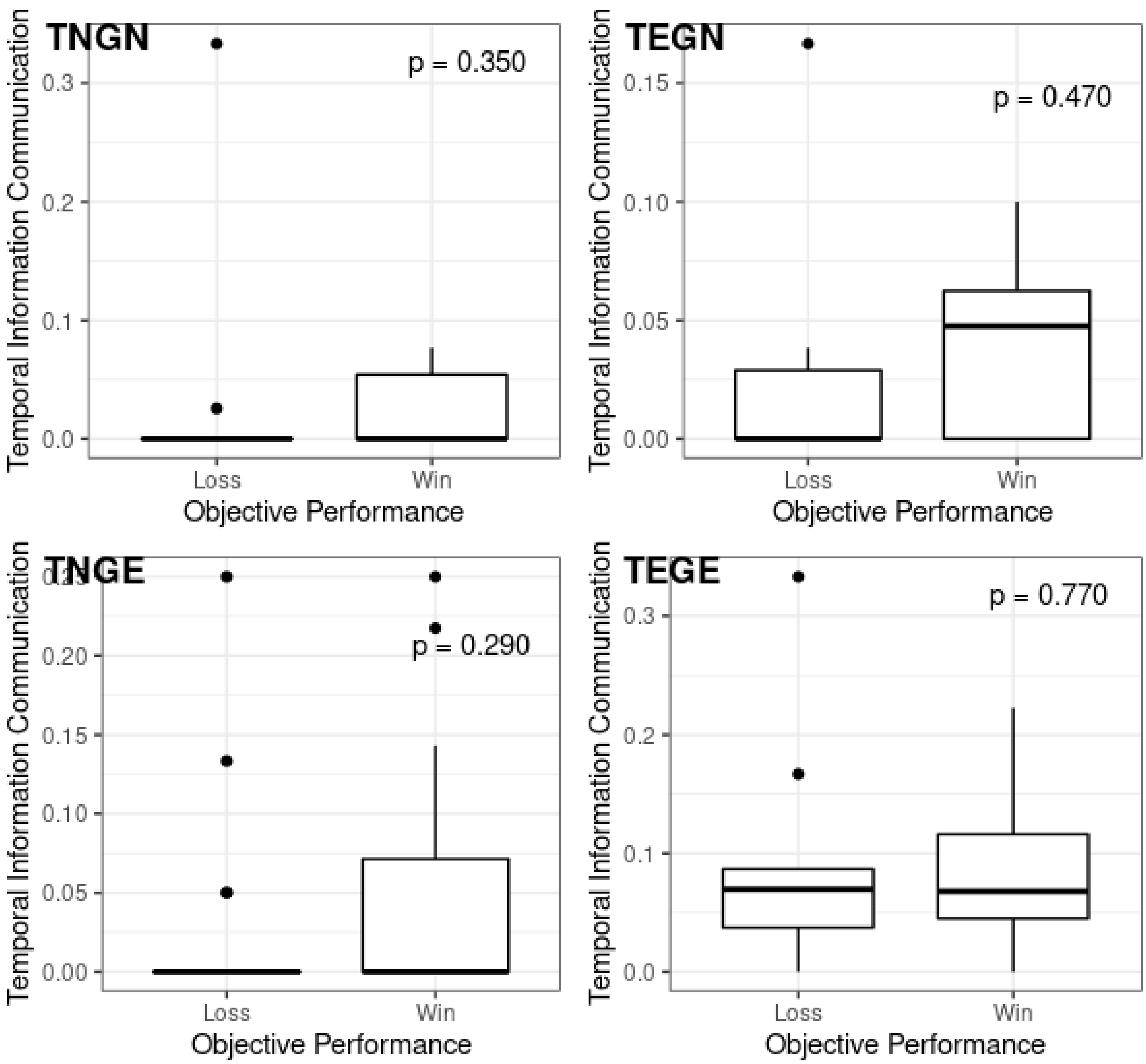

Figure F.14: Boxplots of temporal information communicated by objective performance in each group.

Appendix G

Analysis of Temporal Information Communication, Team Experience, and Game Expertise

Table G.1: two-way ANOVA of temporal information communication as a function of team experience and game expertise.

Source	*df*	Sum of squares	Mean square	F	p
TeamXP	1	0.01	0.01	1.54	0.219
GameXP	1	0.03	0.03	5.12	0.026 *
TeamXP:GameXP	1	< 0.01	< 0.01	0.43	0.517
Error	78	0.41	0.01		
Total	81	0.45			