COORDINATION SIGNAL THEORY:
A FORMAL FRAMEWORK FOR SOCIAL-INFORMATIONAL MECHANISMS OF COORDINATION IN TEAMS

By

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A DISSERTATION

Submitted to
Michigan State University
in partial fulfillment of the requirements
for the degree of

Psychology—Doctor of Philosophy
Computational Mathematics, Science and Engineering—Dual Major

2023

ABSTRACT

Coordination is the essential process by which teams manage the interdependence inherent in teamwork. Existing research has laid a foundation for understanding the processes of team coordination. However, existing coordination theory and empirical research have significant limitations. To address these limitations this dissertation proposes the Coordination Signal Theory, an information-theory based paradigm for understanding the social, motivational, and informational process mechanisms necessary for a team to coordinate. This framework presents theoretical grounding for understanding coordination as an information exchange process, highlighting the central role of social cognition and feedback. Specifically, the CST distinguishes between two forms of coordination (i.e., *in situ* and *a priori*) and considers the contextual conditions that impact their effectiveness. Additionally, coordination has thus far primarily been studied as a static, single-level phenomenon. Existing models of coordination do consider the dynamic, multi-level nature of coordination, but such efforts are yet to be fully explored. The proposed theoretical framework directly addresses these issues presenting two separate formal models of team coordination that focus on the nature of dynamic feedback and the impact of these processes occurring in locally embedded contexts. This work uses these models to present directions for future empirical study and practical application.

Key Words: Coordination, Team Dynamics, Network, Dynamic Systems, Computational Modeling

This dissertation is dedicated to my family:
Liz, Alice, Elliot, Ember, and Robin
Thank you for being my light and joy!

ACKNOWLEDGEMENTS

I want to thank Liz for her tireless efforts editing and formatting this. You are amazing!

I would like to acknowledge the tireless efforts of my various mentors for guiding me through graduate school. Specifically, Steve Kozlowski has been an amazing mentor throughout my time in graduate school and has shaped my understanding of teams and the way we study them. John Hollenbeck has further been an immense support to me in helping me to shape my interests. Greg Ruark has likewise been a tremendous guide. Finally, thanks to Keven Ford. He did an amazing job jumping in and guiding me through my final year of my doctorate education.

I would like to acknowledge my dissertation committee: Kevin Ford (Chair; Psychology), Michael Murillo (CMSE Chair, CMSE), Steve Kozlowski (Psychology), John Hollenbeck (Management), Ekaterina Rapinchuk (CMSE). This was not an easy dissertation evaluate. I am grateful for your efforts. Your comments and suggestions have significantly improved my work.

I gratefully acknowledge the financial support which has made my graduate school possible. The National Defense Science and Engineering Graduate research fellowship program (NDSEG) has had an immense impact on my graduate training. Additionally, I would like to acknowledge financial support from the Army Research Institute (ARI) and the Office of Naval Research (ONR) as well as MSU’s department of psychology; your funding and support have made this research possible. Thank you.

Finally, I would like to express my sincere gratitude to my family, friends, fellow graduate students and church congregation for numerous instances of supporting my work. You have provided countless hours supporting me and my family through this effort. Specifically (in no particular order) thank you to Billy Smith, Ryan Hemsley, Bryan Burgess, Nathan Baker, Rachel Pyram, Ajay Somaraju, David Griffin, Michael Griffin, Carol Griffin, and Bryce Griffin.

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Introduction

Individual commitment to a group effort – that is what makes a team work, a company work, a society work, a civilization work.

-Vince Lombardi

Consider an orchestral arrangement; numerous skilled musicians act in complete harmony to produce amazingly precise and coordinated effort. The dedication, practice, and rehearsal necessary for a polished orchestra to attain its level of prowess is truly a wonder. Considering such feats of exact coordination serves as a compelling backdrop for considering the nature of teams.

Teamwork is a concept of ubiquitous importance within the modern world. As work gets increasingly complex, little in the modern world is accomplished by individuals in isolation. Instead, modern work is characterized by complex, constantly changing demands performed by diverse teams integrating diverse skills and areas of expertise that increasingly include machine agent team members. As such, research on teams and team processes is an active, vibrant area of academic inquiry. This field has been particularly successful at describing antecedent mediators and moderators of team coordination and performance. In doing so, the teams literature has highlighted numerous constructs and relationships of importance.

One of the primary features of a team is its interdependence. Teams differ from simple disconnected groups of individuals due to their dependence on each other. Understanding the role of interdependence in shaping team processes, and the factors that enable a team to manage these interdependencies is therefore critical to the work of studying teams. Coordination – the act of managing interdependence – therefore plays an essential role in a team's functioning and outcomes. Based on this, efforts to understand team processes have led researchers to identify various cognitive and affective emergent team states as well as team behaviors that correlate with team coordination and performance (DeChurch & Mesmer-Magnus, 2010b; Klein & Kozlowski, 2000; Kozlowski & Klein, 2000; Marks et al., 2001). In fact, a rich literature identifies both antecedents of and outcomes associated with coordination (DeChurch & Mesmer-Magnus, 2010b; LePine et al., 2008). However, despite this depth of research, advances in our understanding of coordination are affected by common limitations that have generated conspicuous deficits in our understanding of how teams manage interdependence.

Coordination represents a complex, dynamic phenomenon, where teams must constantly strike a balance between maintaining rehearsed *a priori* plans, beliefs, and strategies to meet the complex demands of interdependent work while responding to and incorporating newly available information in unrehearsed ways, *in situ*. The ever-changing balancing act of coordination is therefore highly dynamic in nature. Moment to moment, individuals must reaffirm or adjust their actions in what collectively becomes a storm of decisions. The reality of coordination is thus much more complex than the typical approaches used to study coordination would suggest. The majority of research on coordination and its impacts describes coordination (as a team emergent state) as being predicted by static characteristics of team cognition (e.g., sharedness of the mental model) and specific actions (e.g., planning, communication, etc.) aimed at facilitating team management of interdependence (Rico et al., 2008, DeChurch & Mesmer-Magnus, 2010b; A. Espinosa et al., 2002). While such research provides valuable insight into coordination, this static aggregate antecedent-outcome variable pairing based approach is limited in its ability to illuminate the dynamic nature of coordination processes or the complexities of the socially embedded multi-level character of team coordination.

These limitations have significant practical import. Existing research has revealed to researchers and practitioners alike that facilitating the development of a shared mental model helps teams coordinate. Additionally, this work shows that efforts to augment team planning and the effectiveness of team communications supports coordination. While valuable, there are numerous practical questions that this work leaves unanswered. Consider just a few such questions: *Mental models are important, but what is it specifically about the mental models that best supports coordination*? The sharedness of a mental model may predict coordination, but I posit that there is more nuance here that the existing work cannot identify. Second, *when should interventions designed to support coordination be applied?* There is a considerable difference between coordination done *in situ* and coordination done *a priori* yet the existing understanding of coordination has little to offer regarding when each approach to coordination will be more effective. Third, *where within a team's social structure should interventions focus*? While coordination necessarily occurs within the context of a team's social structure, the existing research provides limited insight regarding how to practically leverage the social team context to augment coordination. Lastly*, how to facilitate coordination between humans and machines in modern work contexts where machines increasingly play the role of a team member, not just a tool?* The coordination literature to date has little to say regarding the unique complexity of human-machine team (HMT) coordination.

I propose that to more fully understand the theoretical nature and practical drivers of team coordination, this work requires a fundamental shift in scientific philosophy from a construct-oriented perspective to process-mechanism-oriented theory (Grand et al., 2016; Kozlowski & Chao, 2018; Kozlowski, 2022; Olenick et al., 2022). To this end, the primary objective of this dissertation is to present the Coordination Signals Theory (CST), a formal, process-mechanism oriented framework for understanding coordination. Moving beyond constructed-oriented methods and variance models that dominate psychological literature, I propose an explicitly mechanism-oriented theory explicating drivers of team coordination process sequences. Building on this theoretical framework, two complementary formalized mathematical models of team coordination are presented. Each of these models provides powerful theoretical and practical insights into team coordination processes. Furthermore, the formalized nature of these models provides a tool for facilitating greater machine-based awareness of human coordination demands, thereby augmenting HMT coordination effectiveness.

CST advances our understanding of coordination processes by bringing to light the critical role of informational processes in coordination efforts. Moreover, the CST framework highlights distinctions in the contextual effectiveness coordination efforts that occur during a team's action phases vs. those occurring during a team's coordination phase. In conjunction with these theoretical expansions, this framework explicitly incorporates the critical role of context and specifically explicates two contextual characteristics (i.e., complexity and volatility) of work done in teams that have critical impacts on the role and effectiveness of team coordination. These advances provide clear practitioner-relevant insights into the importance of facilitating a coordination-signal-rich environment and further provide clarity on contexts where such efforts will have a greater impact.

Not only does the CST framework highlight the theoretical importance of informational processes and team characteristics such as complexity and volatility, it does so from a dynamic perspective. Dynamics in psychological processes have long been considered important, but are understudied due to the complexities of issues they pose. This framework of coordination is explicitly dynamic. It not only distinguishes between *a priori* and *in situ* coordination efforts, but it models the process of a team coordinating as a dynamic, ever-changing process. Of particular note, this model highlights the theoretical importance of dynamic feedback within coordination, and the first proposed model directly investigates the potential of this feedback to support a cyclical self-amplification of coordination under certain circumstances. This pattern of dynamic feedback has immensely important implications for efforts to augment coordination.

Furthermore, the CST explores the multi-level embeddedness of coordination. Coordination, on some level, is an inherently social phenomenon. Surprisingly, little effort has considered the direct role of social factors in coordination. In the context of coordination research, social features of a team such as trust, shared identity, etc. have been studied as antecedents of coordination, but primarily as distal predictors which have an effect moderated by team cognition (Rico et al., 2008). Such approaches overlook the fact that for team members to coordinate they must not only know what to do to support teammates and manage interdependence, but they must want to help. There are critically important direct social-motivational processes of coordination that are almost entirely overlooked. The proposed CST framework advances our understanding of team coordination by distinguishing between knowing what to do in a given situation and the social motivation for doing it. Further, CST acknowledges that this process is driven by individuals, suggesting that a simple aggregate approach to understanding coordination may overlook the socially embedded nature of individual decisions to coordinate their actions or not. An understanding of the socially embedded nature of coordination provides further important insights into where to apply potential interventions accounting for the critical role of team social structures.

A Process Mechanism Oriented Framework of Coordination

Teamwork… is the fuel that allows common people to attain uncommon results.

-Andrew Carnegie

This chapter presents a review of the team coordination literature to establish a groundwork for understanding and studying coordination from a process mechanism perspective. To this end, it is important to recognize two concepts that are closely related to coordination. These are 1) team performance, and 2) interdependence. After reviewing these concepts this chapter presents a framework for distinguishing between *a priori* and *in situ* forms of coordination. This is foundational to the development of the Coordination Signals Theory.

Foundations of Team Performance

Performance has been described as a primary criterion of organizational research (Kim & Ployhart, 2014; Mathieu & Gilson, 2012), and is the end aim of most organizational interventions. Although in recent years, more humanistic perspectives have become prevalent in the field of organizational psychology (e.g., well-being, diversity and inclusion: Bezrukova et al., 2016; Bliese et al., 2017; Nielsen et al., 2017; Roberson et al., 2017), performance remains a key criterion of the organizational sciences. As such, there is a long and rich history of studying performance in organizations.

Despite being one of the dominant constructs and criteria for organizational research, performance is a highly ambiguous topic. Some authors (i.e., Mathieu et al., 2017; Mathieu & Gilson, 2012) have suggested its ambiguity is important because of the broad array of contexts in which performance is used. No general construct appropriately applies to each situation so there is a need to allow a context-dependent operationalization of performance Therefore, it is imperative to have a clear understanding of what the undergirding principles that define performance are.

Defining performance is a challenge in part because linguistically performance refers to both efforts (behavioral inputs) and effects (outputs). In an attempt to address this ambiguity, Campbell et al. (Campbell et al., 1993) delineated between individual effectiveness (based on the outcomes of individual effort) and individual performance (based on behavioral effort regardless of the outcome). This convention identified the distinction between effort and effect; however, this framework is focused entirely on the individual, and it becomes much more ambiguous when you try to follow this convention to distinguish between collective team effort and collective team outcomes. In a framework that helps address this ambiguity, Beal and colleagues (Beal et al., 2003) distinguished between performance behaviors and performance outcomes as two distinct but closely related forms of performance. Conveniently, these concepts can be used to describe performance at both the individual and team level, making it ideal for discussing a multi-level phenomenon such as coordination and interdependence, while remaining a relevant tool for understanding individual performance contributions.

Individual Performance

At the earliest origins of organizational psychology, researchers have been interested in how to augment individual performance (DeNisi & Murphy, 2017). As just one example, the principles of scientific management espoused by Taylor (1911) provided guidelines and practices for augmenting individual workers' performance. This extremely mechanistic view of work was based on a pessimistic belief about worker motivation and therefore focused on amplifying performance through a rigorous routine. Taylorism took the lack of motivation and laziness of the workers as a given, and therefore did not attempt to augment performance by increasing the overall effort; instead, it provided tools to ensure that the effort of each worker was most efficiently transformed into outputs.

Although Taylorism has largely gone out of favor, the underlying concepts of scientific management are still prevalent in the organizational literature. For example, researchers have shown that making plans and developing work strategies lead to increased job performance (DeChurch & Mesmer-Magnus, 2010b; A. Espinosa et al., 2002; Marks et al., 2001). Similarly, deliberate practice (Macnamara et al., 2014, 2016) and training (Bezrukova et al., 2016; Kim & Ployhart, 2014) are antecedents of job performance. In each case, though there may be some motivational effects, the primary theoretical rationale for improved individual performance is simply the fact that individuals will effectively choose where to spend their effort despite not necessarily caring more or being any more motivated to perform. This concept was well stated by Frank Gilbreth: "Most of the chance improvements in human [performance]… have been hit upon… by men who were lazy—so lazy that every needless step counted" (Kelly, 1920, p. 34).

By contrast, a large body of research highlights the importance of motivational predictors for performance. Much of the early motivational work was based on the tenants of behaviorism (Skinner, 1965). From these perspectives, rewards and punishments are paramount to motivational processes. This suggests that individual job performance can be best affected by using appropriately scaled time rewards and punishments. However, strict behaviorism is not the only historic perspective on motivational antecedents of job performance. As early as the original Hawthorne studies researchers realized that environmental factors play a critical role in workers' willingness to put effort toward their work (Mathieu et al., 2017, 2018). A significant amount of research has built on these early foundations, highlighting the motivational impact of things such as goal setting (Austin & Vancouver, 1996; Bateman et al., 2002; Locke & Latham, 1990), self-efficacy (Bandura, 1994; Katz-Navon & Erez, 2005; Sherer et al., 1982), the fit between person and job characteristics (Greguras & Diefendorff, 2009; Kristof-Brown & Guay, 2011), and perception of one's job (Boswell et al., 2009; Judge et al., 2017, 2017) on performance. Other perspectives have considered the impact of leadership on individual motivation to perform and have found that leader-member exchange (Dunegan et al., 2002; Martin et al., 2016), servant leadership (de Waal & Sivro, 2012; Liden et al., 2014), ethical leadership (Bello, 2012; Huang & Paterson, 2017), and transformational/transactional leadership (Bass et al., 2003; Bono & Judge, 2004; Lowe et al., 1996) are all predictive of individual performance efforts. Thus the job performance literature is consistent with an operational paradigm of performance outcomes and a motivation paradigm of performance effort.

Team Performance

Despite the value and depth of the individual job performance literature, it does not effectively describe the nature of performance in a team. Practices and interventions designed to maximize individual performance may increase the team's ability to achieve its goals (Kozlowski & Bell, 2003; Kozlowski & Klein, 2000), but this is not necessarily the case. For example, consider the difference between a five-person-team basketball game and a one-on-one basketball game. In the one-on-one game, there is no utility to sharing (i.e., passing) the ball, or any form of coordinating one's effort for that matter. By contrast, researchers have demonstrated that basketball teams that do not coordinate tend to perform poorly despite having proficient individuals (Grijalva et al., 2020; Summers et al., 2012). Attempting to maximize the individual performance of each team member is not sufficient to maximize a basketball team's performance and will likely lead to poorer coordination and, thus, reduced performance. This extends directly to modern work settings where team membership is fluid and the boundaries between teams are fuzzy (Bell & Kozlowski, 2002; Mortensen & Haas, 2018).

Explaining these differences, the teams literature has a number of broad models and frameworks that discuss the unique nature of performance in teams. For example, the IPO framework (Marks et al., 2001; Mathieu et al., 2017; Steiner, 1972) was developed as a heuristic model, expressing how a team is a system that takes certain input constructs, processes them, and produces outcome constructs. This model helps to delineate the role of certain constructs as inputs, processes, or outputs. For example, one application of the IPO model describes team adaptation as an important factor of team performance (Burke, 2014). Despite its continued popularity, the base IPO model has various limitations. For example, Ilgen et al. (2005) noted dynamic feedback is an essential component of team performance and concluded that “the I-P-O framework is insufficient for characterizing teams” (p.520). In a bit of a shift from the original IPO model, Marks and colleagues (2001) established distinct transition and action phases in which IPO processes iteratively function. Marks and colleagues further set forth a model of team performance which delineates affective emergent states (e.g., shared moods, cohesiveness, etc.), cognitive emergent states (e.g., shared mental models), and processes (e.g., team planning). This framework more clearly delineates distinctions between the different forms of team constructs, and further emphasizes the importance of interdependence as a key moderator connecting team emergent states and processes with team performance.

These foundational teams theories have been used to shape various team-performance studies. This work has consistently found that, at least in interdependent contexts, factors impacting a team’s ability to work well together, and coordinate efforts are highly important for team-performance outcomes. For example, affective emergent states such as team cohesion (Beal et al., 2003; Evans & Dion, 1991; Grossman et al., 2022) and team conflict (De Dreu & Weingart, 2003; De Wit et al., 2012; O'Neill et al., 2013), cognitive emergent states such as shared mental models (DeChurch & Mesmer-Magnus, 2010a, 2010b; J. R. Turner et al., 2014), and team processes such as team planning (DeChurch & Mesmer-Magnus, 2010b; LePine et al., 2008; Marks et al., 2001) and team communication (Lyons & Popejoy, 2014; Marlow et al., 2018), have all been demonstrated to be important predictors of team-performance outcomes in interdependent teams.

Parallel to individual performance are two potential theoretical mechanisms driving these findings. First, due to interdependence, a team's ability to effectively coordinate their effort will significantly impact the outcomes associated with the efforts of the team members. This is analogous to the operational perspective of performance outcomes described for individuals in line with the mechanisms of various emergent states, including shared mental models and cohesion, and have been found to predict team performance. Such emergent cognition and affect enable greater performance as individual members of a team know how to and choose to act in a way that best supports the team's objectives (A. Espinosa et al., 2002; March, 1991). This is an operational perspective of performance because the individuals are not necessarily more motivated to work harder because of the team context.

The second theoretical mechanism is a social motivational phenomenon. Individuals are motivated to act in accordance with social identities that they internalize (Abrams & Hogg, 1999; Hogg, 2001; Kreiner et al., 2006). Similarly, through affective contagion, it is possible for motivational states to spread among team members (Hennig-Thurau et al., 2006; Wróbel, 2010). In line with social identity theory, this is particularly true if they share an identity. Social contextual forces may drive an individual who is in a cohesive team to have more fully internalized the team's goals and therefore be more motivated to put effort into their respective tasks (Beal et al., 2003). Likewise, conflict – particularly relationship conflict – can isolate individuals from a team identity, leading to reduced motivation to perform in accordance with the team's goals (De Dreu & Weingart, 2003). There is much more that could be said regarding the factors that lead to shared motivation, but for the present purpose, it is sufficient to note that individual performance efforts can be enhanced in a team setting through collective motivational processes that are impacted by both team emergent states and collective identification.

Emergent States

Numerous theories and frameworks for understanding teams have been popularized. One has had a significant impact in shaping our understanding of the nature of work in a team. This is the framework of team-processes and emergent states proposed by Marks and Colleagues (2001). According to this model, teams can be studied in terms of three primary components. These are affective emergent states, cognitive emergent states, and team processes. Affective emergent states are team-level, affective phenomena, such as group positive affect (DeChurch & Mesmer-Magnus, 2010b; Marks et al., 2001), team-efficacy (Gully et al., 2002), and team cohesion (Grossman et al., 2022). An affective state can be said to emerge compositionally (c.f., Kozlowski & Klein, 2000) as the affect of members of the team converges toward a common level. Alternatively, collective divergence across the affective states of team members produces compilational emergence.

Similarly, cognitive states emerge through processes of convergence and divergence (J. R. Turner et al., 2014). Two closely related examples of emergent cognitive states are transactive memory systems and team mental models (Hollenbeck & Spitzmuller, 2012). Both describe how individuals in a team have a mental representation of their team's work. This mental model can converge compositionally, leading to shared team cognition. This is referred to as a team mental model. In other cases, team members do not need to actively participate in each task assigned to the team or know everything that their team members are doing to perform well. In such cases, teams often form distributed mental representations of their work such that they have shared understandings of how their work interacts with team members but do not need to know the specific details of the work performed by others. This is referred to as a transactive memory system. The differences between these two emergent cognitive states (i.e., team mental models and transactive memory systems) are beyond the scope of this dissertation, and the terms will be used interchangeably.

In addition to emergent team states that are affective and cognitive in nature, teams are understood by their processes. A process is a sequence of actions or events that leads to team outcomes (Marks et al., 2001). From an operations perspective, teams are made up of more than one individual who each performs tasks to achieve shared goals (Kozlowski & Bell, 2003). We can see here, that work in a team is defined by team members, the tasks they perform, and the outcomes of these tasks. Team processes are the unique sequence of actions and behaviors of the team that supports these efforts (Kozlowski & Chao, 2018).

Interdependence

In all the work done to study team performance, there are few studies that actively connect individual performance paradigms to the team level. Aggregate measures of individual performance have been used to predict or even represent collective performance (Kozlowski et al., 2013; Kozlowski & Klein, 2000), and such models have been used to justify the effectiveness of interventions designed to improve individual performance as a lever for augmenting the team's performance. However, theoretically, this approach necessitates an additive form of performance that is ignorant of the much more complex reality of interdependence found in most teams. Though the connection between individual and collective performance is sometimes represented as being moderated by interdependence, this too fails to adequately address the complex reality of interdependence.

Interdependence is a defining factor of teams (Griffin, Somaraju, Dishop, et al., 2022; Kozlowski & Ilgen, 2006). As Kozlowski and Bell stated, "Recognition of the central importance of team workflow, and the task interdependence it entails, to team structure and process is a... key characteristic of the organizational perspective on workgroups and teams," (2003, p. 455).

Thus, interdependence is crucial to understanding the nature of teams. However, the current construct-oriented approaches that use an aggregate team report variable to assess the level of interdependence in a team are unable to model the locally embedded process mechanisms driving interdependence’s impact on teams., The current approaches to studying interdependence suffer significant methodological issues and fail to account for the localized embeddedness of interdependence in teams; they are thus unable to study the finer-grained impacts of various patterns of interdependence and the nuances of these interdependence structures (Hemsley & Griffin, 2022).

In a recent set of papers explicating the nature and measurement of interdependence, Griffin et al. (2022a, 2022b) explicitly discuss the complex network of interactions described by interdependence in a team. Such an interdependent reality makes it clear that a purely additive perspective of connecting individual- to team- performance is insufficient to effectively evaluate or theorize about performance in a team. In this paper, the researchers clarify that interdependence takes numerous forms (e.g., task interdependence, outcome interdependence, sequential interdependence, pooled interdependence), many of which have overlapping or ambiguous interpretations. By considering interdependence in a network context we can recognize interdependence as a relational construct such that one entity's performance is impacted by something it "depends on". From this perspective, interdependence across a whole team is not simply an additive measure, but a structural reality that has unique and complex implications for the team.

In the follow-up paper, Griffin et al. (2022b) proposed a formalized representation of interdependence networks which clarifies that each dependency relationship is parameterized by a relationship weight. This generalized formalism for interdependence allows us to represent any interdependent relationship among individuals, tasks, and states, in terms of additive (or pooled), inhibitive (or conjunctive), or facilitative (or disjunctive) relationships. The paper presents a formal state-space model of collective performance which accounts for the complex connections between individual and team-performance outcomes. Whereas the vast majority of studies regarding interdependence use it as a single aggregate measure of a team construct, this dynamic network-based perspective describes interdependence as a mechanism by which complex patterns of performance emerge. Importantly this framework is a generalized framework compatible with numerous conceptualizations of interdependence found in the literature (e.g., Courtright et al., 2015; Shiflett, 1972; Steiner, 1972).

As discussed previously, the team's emergent processes and the work they performed are defined largely by the nature and degree of interdependence in the team (DeChurch & Mesmer-Magnus, 2010b; Stewart & Barrick, 2000). For example, Hollenbeck et al. (2012) built a theoretical typology for teams, followed by Lee and colleagues (2015) who developed an index for defining teams based on their level of "vertical" and "horizontal" interdependence. Illustrating that teams and the work they do are shaped by various forms of interdependence, resource and input independence impact how a team must plan out its efforts. Process interdependence, such as workflow and sequential interdependence, impacts the timing and coordination demands of a team (Van de Ven et al., 1976), while outcome interdependence has important interpersonal effects (Pennings, 1975; Van Der Vegt et al., 2000). To a large extent, if you understand the nature and structure of interdependence in a team, you can understand the nature and function of the team.

Because of the complexities of interdependence, for highly interdependent teams, randomly picking tasks to perform or trying to optimize individual performance independently will often yield poor team performance results. This is well illustrated by considering a basketball team. If everyone tried to optimize their independent performance, they would never pass, never screen, and generally play as if it were a game of 1 vs. 9, not 5 vs. 5. "Teams" behaving in such a way will clearly perform poorly. The interdependent nature of basketball enables one team member to augment the performance of another (Grijalva et al., 2020; Summers et al., 2012). But to do so, the team must act in a coordinated and controlled manner that is responsive to performance feedback. Consistent with these ideas, numerous researchers have explicitly studied the impact of interdependence as a moderator between performance and predictors such as coordination (Rico et al., 2008), team cohesion and emergent affect (Gully et al., 2012), team emergent cognition (DeChurch & Mesmer-Magnus, 2010b; Kozlowski & Ilgen, 2006), and team processes (LePine et al., 2008). As such, interdependence in teams makes team coordination (i.e., the management of dependencies - A. Espinosa et al., 2002) highly consequential and has a significant impact on the observed coordination in teams (Cheng, 1983).

Team Coordination

Given the central importance of interdependence in team functioning and performance, managing interdependence appropriately and effectively is a key factor in shaping the reality of work done by teams. Coordination – which is often defined in terms of a team's ability to manage its dependencies (A. Espinosa et al., 2002) – is therefore a critical factor to understand in efforts to augment team functioning.

Research on the topic of coordination has gained prominence due to its essential role. For example, to facilitate coordination and increase team performance, teams often make plans and assignments for who will do what, how, and when (A. Espinosa et al., 2002). As part of these arrangements, they may make contingency plans for how to handle various potential scenarios. As highlighted by Stout et al. (1999) efforts to generate clear shared plans are an attempt to establish shared models of work across the team, ensuring that there is a clear understanding of each member's role within the work system. This work can be described as transition phase efforts and behaviors to coordinate future work.

Coordination efforts done during a transition phase can be further split into two focuses: 1) individual model development, and 2) relational model development. As Kozlowski et al. (1999) describes, individuals initially focus on their own performance and only afterwards do they start building models based on dyadic relationship and eventually the entire team. The initial individual mental models are established through practice, planning, and assignment. These models dictate who will do what, when, how, and under what circumstances. This is a rigid form of mental model, focused on what one individual needs to do, not how one's tasks relate to others or the greater team working system. By contrast, relational models are typically developed later through a process consisting of team discussions and activities aimed at helping team members recognize their place within the broader team's performance system. Such efforts enable team members to understand how their tasks impact others and help them to be more responsive to each other's needs but do not focus as much on specifics of who will do what and when. Notably, though individual model development often is more prevalent early on and relational later, both forms of model development generally occur concurrently to some extent. Teams differ in their developmental stage (i.e., how early or late in the development process they are) and their overall focus on individual-specific task plans and contingencies, vs. relational models of the teams' work.

In contrast to this transition phase coordination work, team members often coordinate "on the fly" while they are performing their role-essential tasks. Notably, this *in situ* coordination is closely related to the concept of adaptability; however, these are distinct concepts. A team's ability to coordinate *in situ* is likely to enable them to effectively respond to unforeseen shocks, but even in highly stable environments where teams do not need to be highly adaptable, a team may benefit greatly from high levels of *in situ* coordination. While *in situ*, engaged in the team's tasks (i.e., during an action phase - Marks et al., 2001), team members coordinate by both *explicitly* communicating with each other – making requests, stating availability, etc. – and *implicitly* by personally observing team members and acting according to one's mental model of the work to best facilitate team performance (A. Espinosa et al., 2002). In fact, a primary goal of transition phase efforts to develop relational mental models is to augment a team's ability to coordinate *in situ* (during an action phase).

For this reason, I reference *a priori* coordination efforts as those efforts to facilitate plans, task assignments, resource allocations, etc. that were developed before the actual performance scenario. By contrast, I refer to efforts aimed at facilitating "on the fly" coordination as *in situ* coordination efforts regardless of whether the effort occurred during the action phase (e.g., making a request to help with a task) or in a transition phase (e.g., relational mental model development). *In situ* coordination itself only represents the management of interdependence that occurs during an action phase, but I categorize efforts and behaviors aimed at facilitating this type of coordinating as *in situ* coordination efforts regardless of if they occur during an action phase or transition phase. Similarly, *a priori* coordination itself is coordination that originates from decisions made during a transition phase. However, *a priori* coordination efforts would include action phase efforts such as mental rehearsal of one's assigned tasks, as long as it is an effort aimed at facilitating coordination that originated *a priori*.These insights point to the importance of communication and shared mental models for coordination in teams. Additionally, this brings clarity regarding two different focuses of mental model development. However, much is still not understood regarding the nature of coordination, and specifically the processes by which team coordination emerges. I propose the CST, a framework aimed at addressing three key gaps in our understanding of coordination. Firstly, coordination research has dominantly focused on emergent team cognition as an antecedent but has largely overlooked the essential impact of the social context in which coordination occurs, as well as other features of the team's performance context (e.g., complexity and volatility of the context). The proposed CST framework describes the critical role that social factors play in coordination explicit and centerstage while also providing a foundation for understanding the differential impact of coordination based on the team performance context. Secondly, existing research takes a predominantly static approach to understanding coordination which fails to recognize the dynamic nature of coordination. Specific existing coordination research overlooks the impact of dynamic feedback loops in driving patterns of team coordination. CST incorporates principles of dynamics such as feedback, equilibrium, and stability, to develop a theoretical understanding of the dynamics of coordination processes. Lastly, existing research has almost exclusively taken a construct-oriented approach to understand coordination, noting for example the correlations between constructs such as shared mental models and team coordination without more deeply investigating the process mechanisms facilitating the emergence of coordination itself. The proposed model explicitly defines social and information-based process mechanisms by which teams are able to coordinate. This not only highlights predictors and antecedents of coordination but provides a strong theoretical understanding of how coordination could occur. Given the enormous impact that coordination can have on teams and the essential role that teamwork plays it is imperative that research address these gaps to investigate paths for more effectively facilitating team coordination and performance.

It is important to note that the exact definition of coordination is not universally agreed upon. While the notion that coordination relates to a team's ability to manage interdependence is generally accepted, many researchers have proposed much more narrow conceptualizations of coordination. For example, Marks and colleagues (2001) incorporate coordination into their taxonomy of team processes. Their definition of coordination explicitly focuses on timing and sequencing of interdependent actions. A strong association between coordination and timing/sequencing is understandable because many of the conceptualizations of interdependence itself are closely tied to timing and sequencing. Despite this, I suggest that taking a more general interpretation of coordination – consistent with the work of Espinosa et al. (2002), and Rico et al. (2008) – provides valuable insight. Specifically, building on the network-based conceptualization of interdependence espoused by Griffin et al. (2022a, 2022b), sequence and timing specific forms of interdependence can be reconceptualized within a broader network-based paradigm.

This allows us to think of coordination in terms of general efforts to manage the impact of interdependence without being tied to one form of interdependence (e.g., sequential interdependence). The work presented here would apply to a more narrowly defined concept of coordination, but is also applicable more broadly.

None of this is aimed at calling into question the merit of the more narrowly defined conceptualizations of coordination. In fact, future empirical work to test this framework will almost certainly utilize more narrowly defined team processes, including a timing/sequencing-based operationalization of coordination. However, the generalized definition is adequate for the purposes of this dissertation. Specifically, this approach allows us to consider how team processes that are explicitly related to managing interdependence (e.g., planning) are related despite often being considered separately. Furthermore, by using a more generalized paradigm for coordination, this framework lays key foundational ideas that future work will rely on to present a generalized coherent network-based paradigm for understanding interdependence.

Information Theory and Social Mechanisms of Coordination

Alone we can do so little. Together we can do so much.

— Helen Keller

To address existing gaps in the coordination literature, I propose a dynamic model of both cognitive and social process mechanisms driving the emergence of coordination in teams. The proposed CST framework explicates theoretical process-mechanisms by which coordination in a team can occur.

Before presenting the information theory-based paradigm, it is valuable to consider the distinction between *a priori* and *in situ* coordination efforts. The defining distinction here is that *a priori* coordination efforts establish what tasks an individual should perform based on anticipated scenarios that have not yet occurred. Because this coordination occurs at a time separate from the actual performance of tasks it is difficult to manage high levels of precision though *a priori* coordination. On the other hand, *in situ* coordination efforts facilitate teams in making on-the-fly adjustments to the tasks they are performing. Because *in situ* coordination occurs while performing the team tasks, it is more time-sensitive and requires more adaptation, flexibility, and cognitive resources in general. The end goal of both *a priori* and *in situ* coordination efforts is to help team members work in a way that appropriately accounts for interdependence in the team context. As such they are both accurately referred to as coordination efforts. However, they differ significantly in regard to context, available resources, and timing. As such I propose that *a priori* and *in situ* coordination are two distinct and essential components of team coordination efforts. Noting that either approach to coordination is essentially an effort to communicate some information (i.e., needs, requests, availability, objectives, etc.) among team members, I leverage an information theory paradigm (Shannon, 1948) to explore the informational process mechanisms of coordination. I first provide a brief overview of information theory, then describe an information theory-based paradigm for understanding team coordination efforts.

Principles of Information Theory

Information theory is a set of analytical and theoretical tools used to study and understand the conveyance of information. It has had prominent historical impacts on the development of the internet, error-correcting code, robust secure communications, and Bayesian statistics, to name just a few applications. The fundamental unit in information theory is a 'bit' which represents a single yes-no question. Multiple packets of information, or bits, are combined to make up what I will refer to as a signal. Signals are sent from some source to some receiver. Information theory describes how we can understand various forms of communication and informational processes in terms of the ability to convey signals made up of these yes-no bits of information. Information theory is fundamentally interested in the constraints of conveying such signals.

Returning to the concept of coordination, up to this point we have outlined a parsimonious framework for understanding coordination in terms of team processes that either happen during transition phases (i.e., *a priori*) or during action phases (i.e., *in situ*). In incorporating dynamics into this framework it is important to highlight why this may matter. From an information theory perspective, coordination is the process of sharing signals and incorporating information among team members regarding what, when, and how tasks should be performed. For example, making and disseminating an *a priori* action plan is an act of passing on information to each teammate about what they should do and when. Similarly, *in situ* coordination occurs as team members communicate with each other (thereby passing on information) or observe each other (thereby receiving information) and incorporate this information into their plans. Whatever form coordination takes, there is some *coordination signal* being used by the team members to adjust their actions to facilitate each other.

Information theory speaks to the constraints of sending a signal, including the accuracy and costs of such efforts. This perspective applied to coordination highlights three key characteristics of coordination: accuracy (i.e., does the receiver get the correct message), cognitive load (i.e., how much information is being shared), and volatility (i.e., how quickly does the message become inaccurate or obsolete). Information theory is used to formally quantify concepts such as information and therefore provides a powerful foundation to qualitatively describe theoretical concepts such as accuracy, cognitive load, and volatility.

Accuracy represents how likely a recipient of information correctly identifies what the information is saying, or how many bits are correctly interpreted. Coordination accuracy then represents the ability of teammates to accurately identify what their teammates are doing and convey their own needs. Information volatility can be defined as a dynamic aspect of information accuracy representing the extent to which accuracy persists over time. Information load is the amount of information (number of bits) required to convey a given message. For coordination, the information or cognitive load reflects the detail and extent of the coordination signal.

Information Accuracy

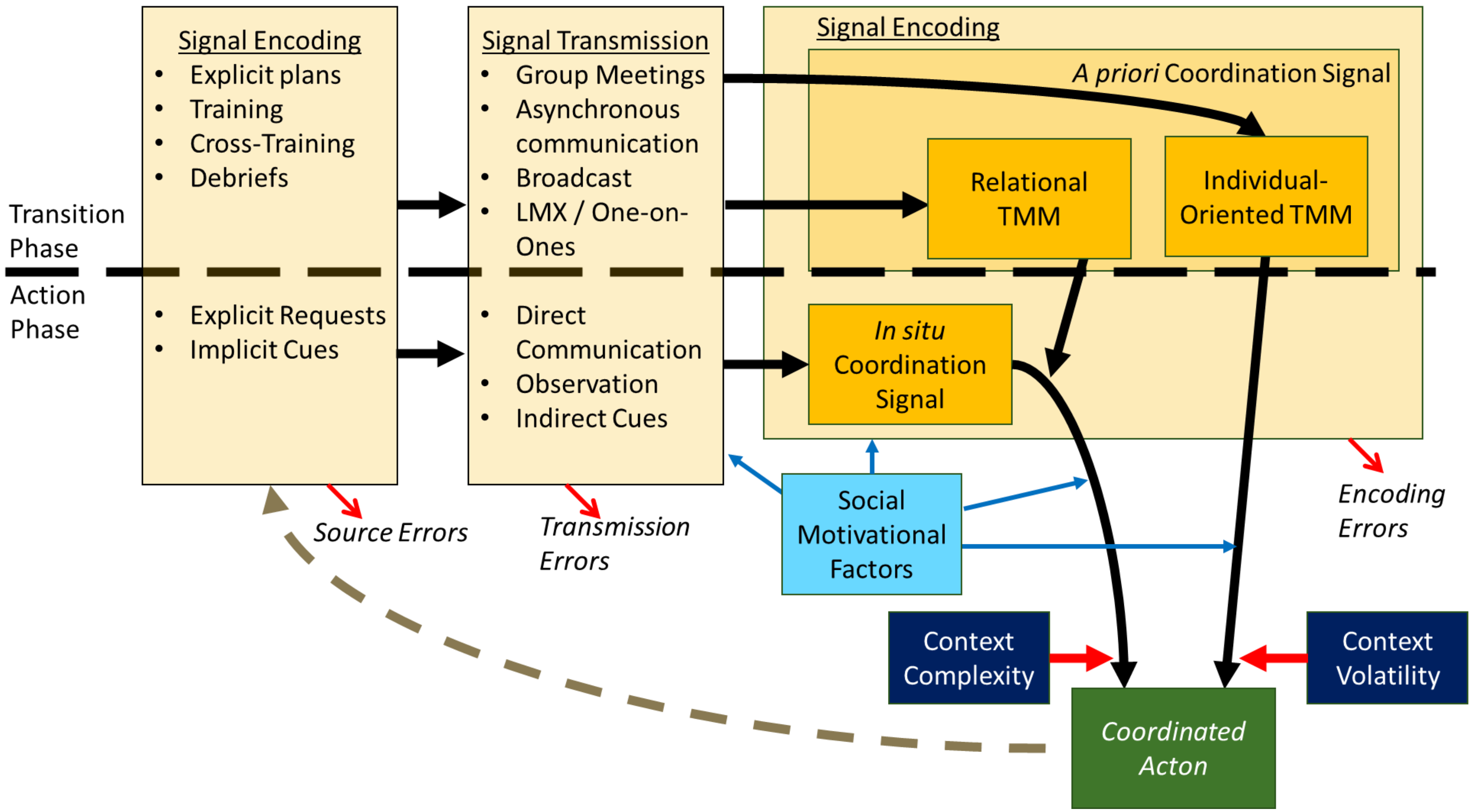
Not every message is accurately interpreted; this is a universal problem that has had enormous consequences throughout history. In information theory, a key characteristic of a given signal is the accuracy with which it is received and interpreted. I define information accuracy to be the extent to which some receiver of a signal can accurately identify the original meaning of the message. Trying to spell out a word over the phone is an excellent example of this. Without visual cues, it is often difficult to differentiate similar-sounding letters (e.g., M and N), and individuals often are forced to repeat the same letter multiple times because the person (or machine) at the other end cannot properly identify the letter being communicated. The same issue is found in much more complicated messages. Consequential, informational inaccuracies occur frequently in teams. For example, in 2012, the large scientific multi-team system responsible for creating a Mars exploratory rover famously mis conveyed measurements of an essential component leading the rover to crash – a coordination mistake that cost over one hundred million dollars (Harish, 2017). Similar stories of costly and deadly mistakes due to poorly communicated information abound.

There are three primary types of inaccuracy 1) transmission errors, 2) source errors, and 3) temporal errors. At its most basic level, a signal's accuracy depends on the ability of the sender to precisely articulate a message (encoding), and the ability of the receiver to interpret it (decoding) and integrate it into their understanding of the world around them. Anything that makes either of these processes (encoding or decoding) more difficult can cause errors to arise and thereby will constrain the signal's accuracy. These inaccuracies represent *transmission errors*.

Having a conversation is a common way to send and receive information about team objectives and processes; however, if the conversation occurs in a room where there are many distractions or background noise, there is a good chance that some of the information will be inaccurately conveyed (i.e., transmission error). Noise, distraction, and different languages/communication styles are all common sources of transmission error.

Figure 1

Visual Representation of Coordination Signal Theory



Note. TMM is for team mental model. Boxes are color coded. Yellow indicates signaling processes. Green indicates coordinated action. Dark blue is for context effects. Light blue is for social motivational factors. Social effects will notably also impact transition phase processes (e.g., TMM development). Three forms of error are indicated, based on the point at which an error develops.

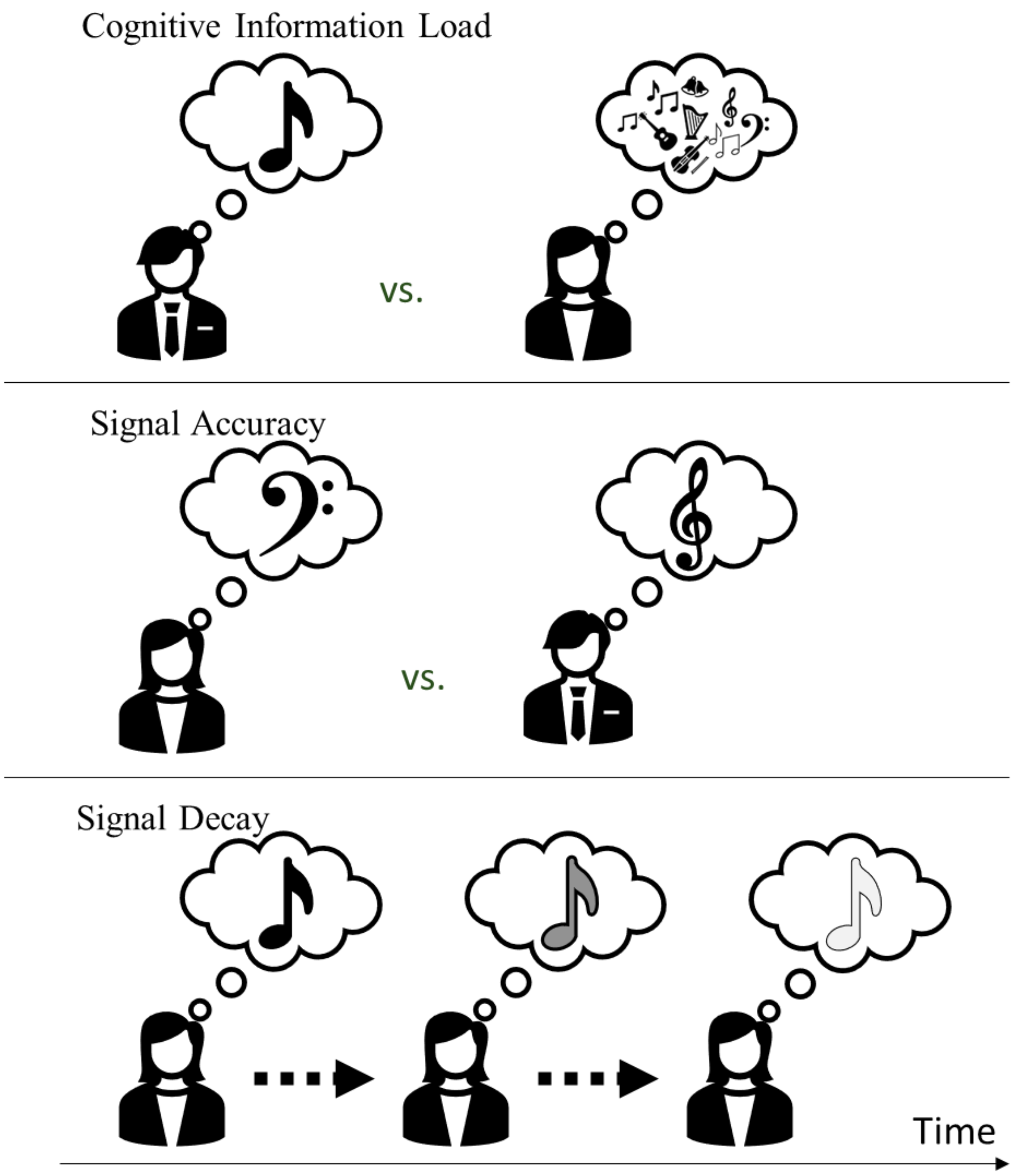
By contrast, many errors occur before the transmission of a signal. If the source of a signal does not have accurate information, the signal they send will be inaccurate. This is a source error. For example, if someone is told the wrong meeting time – regardless of how well they convey that meeting time to others – the information they convey regarding that meeting time will always be inaccurate.

Further complicating the picture, information processing is a dynamic process (Shannon, 1948). An important result of considering coordination in a dynamic framing is the decay of informational accuracy over time. Information tends to become less accurate as time progresses. This is directly tied to the law of entropy (i.e., the law of thermal dynamics that stipulates that systems tend to move toward disorder and chaos.). Over time, small discrepancies between what was expected and what actually happened accumulate, eventually leading to larger discrepancies. Signals that would have been highly accurate at one point lose their accuracy over time. CST uses the phrase *temporal errors* to refer to signal inaccuracies due to this decay (i.e., volatility) in information accuracy.

If a team has a series of tasks that, according to the plan, should each take 30 minutes but really take 35 minutes, the timing of the tasks will differ significantly from the *a priori* plan after just a few tasks are completed. The further out from the starting time you travel, the greater this discrepancy. If the timing of tasks needs to be precise, such discrepancies can become very problematic. Not all sources of accumulated informational error are as systematic as this example. For instance, teams will experience periodic shocks (e.g., a machine at work is down, or a team member is on vacation, etc.) that change the accuracy of the original signal. As time passes these shocks will accumulate, making it more difficult to predict things in the distant future, than in the near-term future.

Figure 2

Illustration of Accuracy Cognitive Load and Information Decay



Note. Figure 2 illustrates three characteristics of signals. Cognitive Information Load (top), is based on the total information needed. Signal accuracy (middle) is based on whether the signal is correctly transmitted, and signal decay (bottom) is a naturally occurring process driven by the principle of entropy.

In this way errors in timing information easily accumulate unless recalibrated regularly. The degradation of information accuracy is a well-known phenomenon (Shannon, 1948; D. Shaw & Davis, 1983; Wicken, 1987) and a key reason that best practices in numerous settings include periodic feedback and recalibration. Even atomic clocks worldwide are recalibrated regularly to combat the entropy-driven decay of informational accuracy. From this perspective, recalibration is a process for clearing out older (and thus less trusted) information used by a system and replacing it with new observations. Each time a system is recalibrated it receives a new set of information as a guidepost to evaluate where things stand and make predictions for the future. Systems that do not periodically recalibrate themselves must rely on very old information, making them problematic to use or trust.

The decay of informational accuracy (i.e., volatility) is a general principle (D. Shaw & Davis, 1983; Wicken, 1987) and is realized differently for distinct situations. This is closely tied to the law of entropy which states that entropy (i.e., uncertainty) must increase. Consider a team example where highly precise information about timing is likely to become inaccurate very quickly. In a dance routine, the particular dance step that should be performed next is an example of precise information that becomes irrelevant just moments later. Thus a dance routine is a highly volatile team performance context. By contrast, software development is relatively much more stable. General details about who is responsible for fixing a particular code error or what software solution they will use will likely remain accurate for hours, days, or even weeks.

The initial accuracy and precision of information are important factors in determining the rate of decay for informational accuracy. The bits of truth scattered in highly inaccurate signals are easily lost due to random contextual changes, etc. Thus, generally speaking, the more accurate an original signal is, the longer it will provide meaningful information. By contrast, highly precise information (e.g., the exact second a train will arrive) is more sensitive than general signals (e.g., the day that a train will arrive).

Coordination in a team requires individuals to respond to each other's needs. This mandates some form of communication. Informational accuracy is a key factor determining the effectiveness of such coordination. If the information shared within a team is not accurate (e.g., the team thinks a person is doing task A, but they are doing task B), coordination is clearly impaired if not completely inhibited. Noise, distractions, misunderstandings, and time itself can all contribute to the accuracy or inaccuracy of the information conveyed by a team while trying to coordinate. While many of these factors contributing to the breakdown of information accuracy are unavoidable (e.g., random events) there are various strategies that can effectively shelter the informational accuracy of coordination signals.

One strategy to maintain or increase information accuracy over time is to repeat a signal. This is something done in both computer communications (e.g., error-correcting code: Hamming, 1950) as well as interpersonal conversations (Stephens & Rains, 2011). Informational inaccuracies due to encoding (the source's attempt to share the information) and decoding (the receiver's attempt to understand the signal) issues become much less prevalent with repeated signals because random events that lead to encoding and decoding problems are unlikely to be randomly repeated. While repeated signals help minimize encoding/decoding signal error, this does not fix issues that arise when the originator of the signal has inaccurate information to begin with. One strategy to address source-inaccuracies is the use of multiple sources of information (Wang & Zhu, 1998). Although this practice is particularly prevalent in electronic communications, the idea applies to communications broadly. In particular, CST claims that if one seeks information from multiple sources within a team context, they are more likely to get an accurate signal even if some of the information sources are not entirely reliable.

Other strategies that increase informational accuracy are communication protocols. If a person is expecting to receive a signal, they can prepare for it and are more likely to receive it accurately. Establishing communication norms and coordination processes during a transition phase (relational model development) can reduce the number of errors that arise during *in situ* communications. One last strategy for maintaining the accuracy of a message is to actively propitiate it. For example, a team can set a schedule for when specific tasks will be started. Although there will be "bumps" in the process of completing the tasks if each team member actively works toward sticking to the exact schedule (i.e., instead of letting the information be descriptive of what to expect from others, letting it be prescriptive for themselves) the natural decay of accuracy may be stymied. There will still, most likely, be problems that arise as even flexible schedules become difficult to meet so the information's accuracy will generally still decay; however, active efforts to maintain the accuracy of a signal message can help maintain the signal's accuracy, making it usable for longer.

Information Load

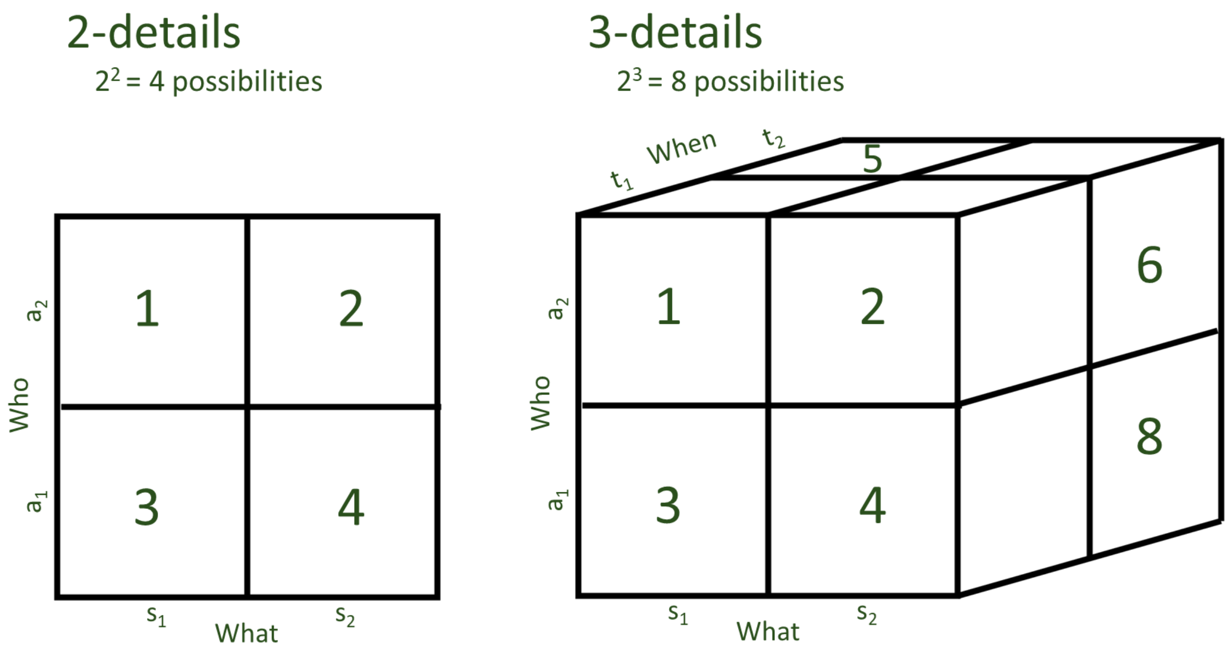
The accuracy of information is closely related to the quantity of information in a message. According to information theory, the clearer and more detailed a message you want to send, the more packets of information are necessary. For example, simply telling someone to turn right or turn left requires exactly one bit or package of information. By contrast, telling someone exactly what letter on a keyboard to press requires five bits of information. This is because it requires at least five different yes-no questions to precisely convey a message that identifies one out of 26 options (i.e., $\log_2 26 \approx 5$). Each possibility a signal can distinguish between increases the complexity of the necessary signal. Generally, each yes-no question can double the number of distinguishable options that can be conveyed by a single signal.

In the context of coordination, numerous ideas and concepts are often delivered through some communication signal. For example, consider a case where there are three members of a team (Anne, Bob, and Carter) who must each perform one of three tasks (K1, K2, and K3). The information required to share exactly which task will be accomplished by whom requires only two bits of information for each team member (six total). In reality, coordination is rarely this simple. Usually, individuals not only need to know what they are doing, but when, who they will work with, and what resources they have access to (Bachrach et al., 2018; Hollenbeck & Spitzmuller, 2012). Additionally, tasks can sometimes be performed in numerous ways and individuals may be able to engage in more than one task at a time. Each of these details increases the complexity of the signal necessary to coordinate.

We can think of a team's task plan as being made up of multiple distinct elements (e.g., Anne performs task S_1). The general rule is that the amount of information required to convey a single element of a plan grows logarithmically with the total number of possibilities it can distinguish. A team's plans rarely are conveyed by just one option. Instead, a team will have plans for different team members performing different tasks at different times under different contingencies. The combination of these distinct elements makes up the full plan – a mental model. A complete plan often includes information regarding multiple such elements; thus the total information required to convey a complete action plan is significantly higher than the information required to convey individual elements of a plan.

Figure 3

Illustration of Information Load



Note. Two bits of information can convey a signal with four potential options. Similarly, three bits of information can convey a signal with eight potential options. Thus, to identify one of a set of options requires a signal that has an information load that grows logarithmically with the number of options. However, fully conveying a plan (e.g., conveying what each person does at each time) requires significantly more information.

The total information required to convey a complete plan is proportional to the total number of elements that must be conveyed. Conveying a plan with ten elements has an information load ten times higher than conveying a plan with a single element. Many plans will have multiple factors that each must be fully stipulated. For example, if we need to know exactly what each of three members of the team will be doing on a given day, this will require an information load three times greater than simply conveying what one person must do. If there are three times (e.g., morning, afternoon, and evening) that need to be planned out for each team member, the total information load required to share a complete plan of who is doing what and when would triple because the plan would need to convey the same amount of information for each timeframe. Following this pattern, the information required to convey a full plan will increase exponentially with the number of elements that are being fully stipulated. If the timing needed to be more precise (e.g., hourly instead of three times a day) this information load would increase 24-fold instead. Contingencies further increase the information load of a team's plan significantly, as each contingency requires a plan that will stipulate a whole new set of elements of a plan.

It is worth noting here a connection between load and accuracy. Shifting from three timeframes to 24 timeframes allows a plan to have significantly more precision (i.e., temporal accuracy), but levies a significantly higher information load. The amount of information shared is thereby directly related to the maximum amount of accuracy achievable by a signal. Limitations to information accuracy can often be mitigated or suppressed by increasing the amount of information shared.

Information theory provides a way to understand the costs and barriers associated with an information-sharing activity such as coordination. If a team member needs only a go/no-go message it requires very few cognitive resources to send, receive, and interpret. On the other hand, a detailed accurate description of what everyone in the team is doing, when, where, and how complete with contingencies and backup plans will require substantially more information and consequently put a much higher cognitive load on the team members involved.

CST uses the term Cognitive Information Load (CIL) to describe how much information (Shannon, 1948) a coordination task requires. This term emphasizes the fact that to respond to a coordination signal, individuals must cognitively process it. CIL is important in determining both what forms of coordination are possible and how effective they will be. Research has shown that cognitively demanding tasks inhibit each other, such that if someone is engaged in high load tasks (e.g., conveying a very detailed plan to a team member) they will be inhibited in their ability to perform other cognitively loaded tasks (M. L. Shaw & Shaw, 1977). This suggests that while coordinated effort may amplify the effectiveness of a team, it has its own cost as well as the potential to reduce overall performance. There is necessarily a balance to coordination efforts because sharing too much information exacts a high cognitive cost while sharing too little can lead to significant process losses. The exact nature of this balance is a question of considerable interest and is determined by 1) the cost associated with sharing information, 2) the accuracy of the information, 3) the rate of informational decay in the team, and 4) the nature of interdependency in the team (how much my team will be hurt by missing or inaccurate information).

A Social/Information Based Paradigm of Coordination

The impact of coordination on teams depends significantly on contextual factors. For example, coordination for teams with complex, multi-faceted interdependence structures will differ greatly from coordination in simpler team contexts. Complexity will require more detail to effectively coordinate. Similarly, coordination in teams that function in fast-paced, volatile contexts where task demands are constantly changing will differ significantly from those that function in more stable contexts. I map these ideas onto a single circumplex with the volatility/stability of the context on one axis and the complexity/stability on the other (See Figure 4).

Taking these concepts together, we can map out different work contexts based on their overall sensitivity to precision in timing (volatility) and their detail requirements (complexity). For example, software engineering is highly detail-sensitive – you often must know precisely what packages and functions various components of software are using to effectively coordinate. However, software development rarely requires highly precise coordination (in the order of minutes or seconds). By contrast, a team rowing a boat requires very little detail, but tremendous precision in timing.

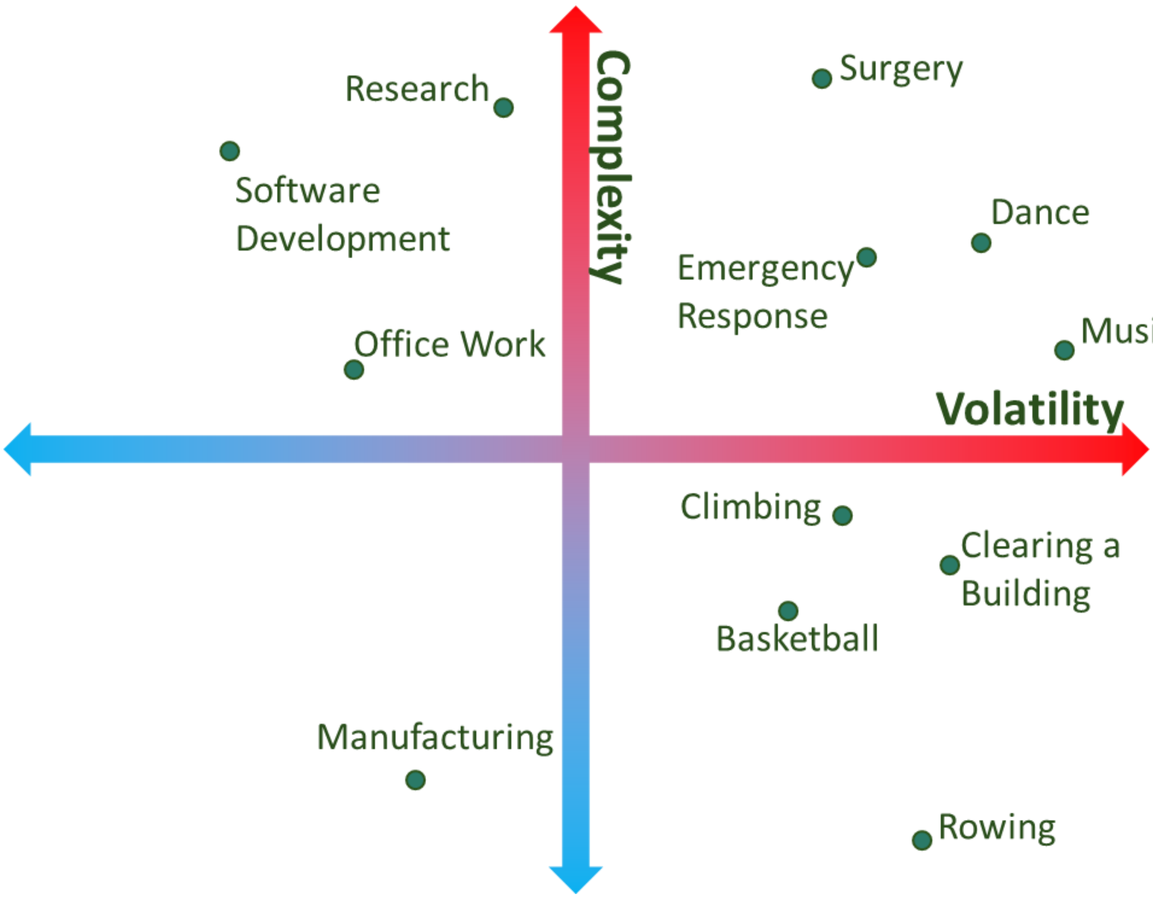
A Priori and In Situ Coordination

Information load and information accuracy strongly affect *a priori* and *in situ* coordination. In particular, these effects will depend on the complexity and volatility of the team performance context. That is, complex vs. volatile contexts will be differentially affected by *a priori* vs. *in situ* coordination.

As noted previously, *a priori* coordination occurs during transition phases. It is less proximal to the actual moment of performance and therefore subject to more temporal degradation of information. For this reason it requires significantly more effort to maintain the accuracy of coordination signals that originate *a priori*. It is therefore often less effective to coordinate highly precise information *a priori* that is prone to informational decay, such as exact task timing information, required for synchronized task performance. When such information is coordinated beforehand, teams must actively dedicate effort to maintaining the integrity of the established schedule while accounting for delays and other issues that will arise during the performance of the tasks. CST specifically posits that these issues are particularly prominent in highly volatile team contexts where task demands switch frequently and precision is essential to effective coordination.

Figure 4

Mapping of Teamwork Based on Complexity and Volatility



Note. Dots in the figure represent an illustration of how different work contexts experience different levels of volatility and complexity. Timing-sensitive, volatile contexts (on the right) will generally be more reliant on effective *in situ* coordination efforts, while detail-oriented, complex contexts (top) will generally be more reliant on strong *a priori* coordination efforts.

On the other hand, *a priori* planning often occurs when there are weak time constraints, and little additional task-based drain on cognitive resources. Consequently, *a priori* coordination effort is well suited for highly complex coordination that requires more effort to make decisions about and plan out. For the same reasons, *a priori* coordination is also less sensitive to Informational Cognitive Load than *in situ* coordination. As such, *a priori* coordination is expected to be more effective at addressing coordination demands for teams functioning in highly complex contexts. Thus, although the natural decay of informational accuracy makes it difficult to accurately convey precise details, such as timing, through *a priori* coordination, it is well suited for providing detailed plans and contingencies that are not sensitive to precision in time.

In contrast, *in situ* coordination efforts are aimed at facilitating changes to the tasks that team members perform during action phases. As such, it is less sensitive to the temporal degradation of information accuracy. This is because the information will be used by team members relatively close in time to when the signal is generated. Highly volatile team contexts will effectively meet coordination demands through *in situ* coordination. However, as noted previously, given that task changes associated with *in situ* coordination occur during the actual performance of a team's tasks, it will generally happen while team members' cognitive resources are being taxed. When a basketball player is in the middle of a drive, they do not stop to convey the entire play to their teammates. Instead, they rely on simple *in situ* signals from each other to leverage the shared models that they have already developed. Despite generally being less sensitive to the decay of informational accuracy over time, *in situ* coordination is more sensitive to the cognitive load of coordination. It is therefore unlikely that team members establish complex, detailed plans during their performance of other tasks. Thus, *in situ* coordination efforts are generally less effective at meeting the needs of high complexity team performance contexts.

Taken together, *a priori* coordination is well suited for establishing complex and detailed plans and schedules. Although such plans are not always discussed in terms of transactive memory systems or shared mental models, one of the goals of such efforts can be described as establishing clear shared mental models or transactive memory systems among a team (Stout et al., 1999). *In situ* coordination on the other hand is best suited for precise (volatile) yet simple coordination efforts. Team members can take small signals (either implicitly via observation, or explicitly through active cues and communication) to adjust work efforts in a precise manner. But coordinating complicated plans would quickly tax individual cognitive resources, thereby adversely impacting performance.

Importantly the two forms of coordination are not independent. For example, researchers have found that *in situ* coordination efforts depend on the quality of a team's shared mental models and plans (Stout et al., 1999). Well-established and detailed plans about how the team functions enable team members to use simple (i.e., low cognitive load) *in situ* coordination effectively despite the complexity of the context. Similarly, the ability to coordinate *in situ* enables teams to focus on establishing more general models of team functioning *a priori* instead of dedicating excessive team resources toward making and maintaining precise *a priori* plans. Hence, *a priori* and *in situ* coordination are dependent on each other, but clearly distinct in nature and limitations, necessitating studying them as distinct, yet related concepts.

Moreover, just because one form of coordination effort is more effective in one context than another doesn't mean that the other is obsolete. In highly volatile performance contexts where individuals are unable to interact or communicate, highly precise *a priori* coordination can take the place of *in situ* coordination. For example, highly trained special operations teams in the military often must function in a highly coordinated way with highly limited communications. On the other hand, teams that are extremely effective at *in situ* coordination may require less *a priori* coordination effort than would be expected.

As illustrated in Figure 4, various forms of work are mapped onto a two-dimensional space based on their coordination needs. *In situ* coordination efforts will be more effective than *a priori* coordination for teams that are highly timing sensitive (volatile – right). Similarly, *a priori* coordination will be important for highly detail-sensitive (complex – top) work. Those work contexts that are both detail and timing-sensitive likely require a high degree of both *in situ* and *a priori* coordination.

Social Mechanisms of Coordination

One important insight from the information theory perspective of coordination is the essential role of social mechanisms of coordination. For the most part, the nature of social interactions and social relationships have been divorced from the mechanisms driving the emergence of coordination. For instance, constructs such as trust and group efficacy are often used as mediators for shared team cognition (DeChurch & Mesmer-Magnus, 2010b), but not incorporated as direct antecedents of coordination itself. This focuses on the idea that coordination is primarily based on having access to an accurate shared mental model, but fails to account for the social motivation for coordination.

However, the information theory perspective of these mechanisms highlights an important fact. These processes are not only informational, but social. The process of sharing and responding to signals from teammates requires individuals to communicate with each other. Furthermore, team members must respond to those signals. The extent to which individuals actively seek to share and respond to signals from each other is clearly crucial to a team's ability to coordinate but is for the most part not included in models of coordination. I explicitly suggest coordination is driven in part by access to specific information (what to do when) and in part by social factors. I will refer to these social factors in aggregate as the level of social responsiveness among team members, or the social coupling strength.

There are various social factors that could impact team members propensity to communicate with and respond to coordination signals from each other. For example, Social

Identity Theory (Abrams & Hogg, 1999; Hogg, 2001; Stets & Burke, 2000) and Self Categorization Theory (J. C. Turner, 2010; J. C. Turner et al., 1987) provide foundational insights into identity-based mechanisms where individuals will selectively respond more to people they identify with. Other social factors that could impact team members' level of responsiveness to each other include trust (Mishra, 1996; Schelble et al., 2022), cohesion (Grossman et al., 2022; Gully et al., 2012), conflict (O'Neill et al., 2013), and Leader-Member Exchange (Le Blanc & González-Romá, 2012), just to name a few.

The exact social mechanisms at play are not the focus of this dissertation, but instead the interplay between such social mechanisms and informational processes as they pertain to team coordination. As such, I will use the generic term Social Responsiveness (SR) to refer to the extent in which individuals share coordination signals, recognize those signals, and in turn respond to those signals. Future work will need to explicate the various social mechanisms that could be at play in more detail.

Coordination Amplification through Signal Exchange Reinforcement (CASER)

An individual can make a change, but a team can make a revolution.

― Amit Kalantri

Due to the emergent nature of coordination, it is necessarily a dynamic phenomenon (Cronin, 2015; DeShon, 2012; Kozlowski & Chao, 2018; Xu et al., 2020) yet existing research on team coordination is largely static in nature (DeChurch & Mesmer-Magnus, 2010a; A. Espinosa et al., 2002; Rico et al., 2008; Van de Ven et al., 1976). In failing to study coordination as a continual, dynamic process occurring contemporaneously with teamwork processes, the coordination literature cannot adequately address the nuances of the complex mechanisms for team coordination (DeShon, 2012; Xu et al., 2020) including the role of feedback and social influence on coordination.

I propose that under the right circumstances, teams can experience a form of positive coordination feedback where signals are reinforced through reciprocal exchange with team members. This process leads to a self-sustaining level of amplified coordination. The present chapter considers the conditions under which such a phenomenon (Coordination Amplification through Signal Exchange Reinforcement) would be consistent with the CST paradigm for coordination. Various dynamic systems found in nature and human populations exhibit a dynamic pattern of feedback. Feedback loops are responsible for numerous phenomena. Negative feedback loops are in some form present in every naturally occurring stable phenomenon. Positive feedback loops tend to be present in cases of instability, dramatic change, and self-propagating phenomena. Given the prominence and importance of such feedback features throughout the natural world, the potential role of feedback in governing/driving patterns of team coordination is of considerable interest.

Investigating the dynamic nature of coordination requires an understanding of the systems at play and the mechanisms driving the observed relationships. This can be much better understood using a systems thinking or process-mechanism oriented approach (Burke, 2014; Frank & Fahrbach, 1999; Griffin, Somaraju, Olenick, et al., 2022; Kozlowski et al., 2013; Olenick et al., 2022). Formal process-mechanism oriented theory is a powerful tool for developing a deeper understanding of a phenomenon and considering the implications of a proposed theory (Kozlowski & Chao, 2018) particularly with regard to dynamics. This dissertation presents two formal process-mechanism oriented models of coordination for this dissertation. In this chapter I propose the CASER model, a novel theoretical framework for the process mechanisms driving the emergence of socially amplified coordination through dynamic feedback. In doing so, this work considers the complexity and dynamics of coordination and team performance in a way that traditional approaches could not.

Importantly, this work also highlights the importance of the multi-level social embeddedness to the coordination process. Coordination is an inherently social process that cannot be entirely understood by considering a team in aggregate. Motivation to coordinate, and decisions regarding what task to perform are necessarily strongly influenced by individual preferences and dyadic relationships. The present model relies on a simplistic aggregate approach but explicitly acknowledges the social nature of coordination. In doing so, it sets the foundation for the second model (see next chapter) which uses a network-based paradigm to study coordination.

The results of this work are theoretical, and until properly combined with empirical validation should be treated as purely theoretical. Despite its limitations, such work has a profound ability to extend our understanding of social and psychological phenomena. Various discussions on the values, limitations, and practices of formal theorizing and computational modeling are present within the literature (Olenick et al., 2022; Vancouver & Weinhardt, 2012).

The purpose of the present CASER model is three-fold. First, this model explicitly demonstrates the role of feedback in synergistically amplifying team coordination. Secondly, this model serves as a first test for distinctions between *a priori* and *in situ* coordination effort. Lastly, this model explicitly explores the essential role of social factors in driving coordinated team behavior. As a team-level model this work is more similar to existing models of coordination (e.g., Entin & Serfaty, 1999; A. Espinosa et al., 2002; Rico et al., 2008) and therefore provides a bridge from the existing literature to the more mathematically intense second model found in later chapters. Because of this, this team-level model will be easier to empirically validate.

The second model (i.e., the Coordination Signal Network Model or CSN model), discussed in the following chapter, considers the same type of phenomenon on the individual/dyadic level, and investigates theoretical dyadic process mechanisms driving team coordination. Whereas the CASER model is simpler and interfaces more directly with existing literature, the CSN model provides a more in-depth investigation into the role of interdependence and the emergence of synchronicity in teams. This second model is more difficult to directly test empirically, but as I discuss below, it has the potential to inform teamwork design in a powerful way. Specifically, there is tremendous potential for this work to impact practice in the human-agent teams domain.

Theoretical Development

From the information theory perspective, coordinated behavior relies on signals, and in turn produces its own coordination signals. Thus at least some of the outputs of coordinated behavior act as its own inputs. This input-output pairing is the hallmark of a system that will experience a positive feedback loop. Researchers have studied various such feedback loops. If these feedback loops are present, team coordination phenomenon will have a dramatic effect on the expected behavior of team coordination over time, as well as shaping the effectiveness of various coordination-oriented interventions.

A LASER represents a well-studied system that I believe makes a strong analogy for team coordination phenomenon (i.e., CASER). Specifically, I claim that the same general principles enabling a LASER to produce its amplified, cohesive light apply broadly to teams that are performing interdependent task work. Acknowledging that the reader is likely unfamiliar with how a LASER works, this analogy is discussed in greater detail in Appendix A. It is sufficient for the reader to know that LASERs provide a framework for understanding how a positive feedback loop can lead the system to produce sudden, discontinuous, and dramatic shifts in output. The formalized CASER model found in this chapter employs this analogy for understanding the potential nature of self-amplifying coordination processes. In doing so, I propose a process-mechanism-based theory of team coordination. In this chapter, I first discuss the core mechanisms and components of the framework. Next, I present a formal mathematical model of team-level coordination along with a dynamic systems analysis of the model. Finally, this chapter concludes by discussing the various contributions and implications of this formal theory.

The Social Mechanisms of Coordination

The CASER model is built around the concept that there are three psycho-social phenomena central to the emergence of coordinated effort. In addition to these three main mechanisms, I briefly highlight three additional mechanisms related to coordination signal. First, individuals are motivated. The scientific literature on motivation is both broad and deep, and a full review of these topics is well beyond the scope of this dissertation (for reviews see: Kanfer et al., 2017; Park et al., 2013). Instead, I will speak very generally. For the moment, it is sufficient to note that individuals can be put into a motivated state where they are ready and willing to do work aimed at achieving something. There is generally some motivational stimulus responsible for putting the individuals in such a state. For example, work compensation (Landry et al., 2017), team goal-setting exercises (Park et al., 2013), interactions with transformational leaders (Lowe et al., 1996), or realization of self-autonomy (Deci & Ryan, 2000), self-efficacy (Bandura, 1994; Vancouver & Purl, 2017), and expectancy (Van Eerde & Thierry, 1996; Vroom, 1964) can each act as a stimulus that motivates people to perform work. This stimulus can be internal (i.e., I come to recognize my autonomy) or external (i.e., a pay-for-performance system); they can also be intrinsic or extrinsic (Deci & Ryan, 2000). The point is simply that individuals in a team are motivated by something to act. If there is no motivation or cause for an individual to act, I claim that there can be no meaningful coordination.

Importantly the motivational stimulus that puts an individual into a "motivated state" can take a social form, coming from one's teammates. Exposure to motivated others may encourage teammates who are otherwise amotivated to act. This may occur through a process of affective contagion (Wróbel, 2010), social cognitive learning (Bandura, 1991), or some other psycho-social process influencing individual instrumentalities, expectancies, or valences (Vroom, 1964). While the social mechanisms of motivational contagion are of interest, a thorough discussion of this topic is reserved for future work. For now, it is sufficient to simply recognize that individuals can be motivated by something (or someone) to act, and in particular, exposure to motivated teammates can increase one's own motivation. This internalization of some motivational stimulus is a key factor in enabling team members to act in a goal-directed or coordinated manner.

Mechanism 1: Motivational Internalization. *Individuals become willing to allocate effort toward team tasks as they are exposed to some form of motivational stimulus.*

After an individual has become “energized” (i.e., motivated) and determined to act, the individual must determine what to do. *A priori* coordination and individually-oriented mental models will play a large part in determining at baseline what task an individual will consider pursuing and how. However, beyond outlining what tasks are possible for someone to do, the specific task that an individual engages in will be determined largely based on the individual’s objectives/preferences as well as the information received from their context including from their team members (i.e., *in situ* coordination). When there is no communication or signal that allows team members to act in correspondence with one another (i.e., *in situ* coordination is restricted), workers will necessarily have to individually determine among the possible courses of action outlined by their mental models of the work context. Sharedness of mental models is a key to coordination in such scenarios. In this way, *a priori* coordination efforts serve to set some boundaries around the potential actions that an individual will take, thus establishing a baseline level or coordinated action that can be expected to occur. Nevertheless, depending on the detail and precision of these plans, they may give workers considerable latitude for interpretation.

Individually directed action occurs when individuals act according to non-shared priorities, objectives, or beliefs regarding what team members will do. In a given performance episode, if individuals are unable to respond to/communicate with team members (i.e., *in situ* coordination efforts), the actions individuals perform will necessarily be determined by internally elected priorities, preferences, and beliefs (DeShon & Gillespie, 2005). This lack of coordination signal may be driven by obstacles to *in situ* coordination efforts; however, in many teams, constantly changing task demands (i.e., volatility) will reduce the longevity and thus the availability of coordination signals. Notably, even if a team has an accurate and shared mental model, without clear cues regarding what other members of the team are doing, it is difficult to act in a fully coordinated manner (Van de Ven et al., 1976). This is particularly true in highly volatile contexts, where team task demands change frequently. Thus, for teams performing in volatile contexts in the absence of clear coordinating signals (whether implicit or explicit), individuals will generally act in uncoordinated ways based on motivation in primarily an individualized manner. The impact of individually directed performance depends largely on the nature of interdependence in the team. A team where tasks greatly inhibit or facilitate each other requires precise coordination. In such work environments, coordination is essential and the pursuit of individual preferences and priorities may lead to significant process losses.

Additionally, team members rely on social feedback and cues in driving individual motivation. When there is little or no coordination signal available, individuals will experience ambiguity that could have significant impacts on their motivation. For instance, as described in expectancy theory (Van Eerde & Thierry, 1996; Vroom, 1964), control theory (Carver & Scheier, 1982), and self-regulation more broadly (Lord et al., 2010), the ambiguity that a team member feels when provided little or no feedback regarding how their efforts relate to the work of the team will negatively impact their motivation to perform their tasks aimed at supporting team objectives. By contrast, self-determination theory would suggest that the autonomy afforded to individuals in such scenarios would greatly enhance their motivation to perform tasks that they personally value (Deci & Ryan, 2000). Additionally, various contextual factors will have a large impact in determining individual preferences and priorities. For example, DeShon and colleagues found that socio-contextual cues (i.e., providing individual vs. team focused feedback) play an important role in determining whether an individual will act in a self-oriented or team-oriented manner (DeShon et al., 2004). Taken together this suggests that when there are strong competing individuals vs. team goals, a lack of real-time feedback or communications may prompt individuals to shift toward more personal priorities. Although such individually directed and individually motivated actions can be highly valuable to the team, such efforts are unlikely to be well aligned, leading to significant process losses in highly interdependent team work contexts.

I refer to such individually directed/motivated action as spontaneous effort. This term reflects the nature of the effort being internally driven, and not done in response to some cue or signal. The stronger the discrepancy between individual and team objectives, as well as the stronger the discrepancy in various motivational factors such as the valence associated with those goals, the more individuals will act "spontaneously" in accordance with individually elective preferences and priorities, instead of being prepared to respond to team coordination signals. Additionally, volatility and weak *in situ* coordination efforts can increase the extent to which individuals are expected to produce "spontaneous effort".

Mechanism 2: Spontaneous Effort. *Motivated individuals will act according to individual goals and uncoordinated, individualized perceptions of team goals in the absence of cues or communication facilitating team coordination.*

By contrast, when teams engage in stronger *in situ* coordination efforts or teams are less volatile in their tasks, individuals will have crucial information regarding the team's work processes available to them. This enables teams to coordinate their efforts more precisely in ways that facilitate team performance. Specifically, as motivated individuals are exposed to coordination signals from others they will be more likely to act in a coordinated manner. Exposure here represents the process of sharing information inherent in *in situ* coordination. As discussed previously, the *in situ* coordination described may take various forms, including passive observation of one's teammates or explicit active communication with them (A. Espinosa et al., 2002). As team members individually go about their work, they will adjust the tasks and activities that they engage in in such a way as to manage dependencies and better facilitate the efforts of the team as a whole (Cheng, 1983; A. Espinosa et al., 2002; Rico et al., 2008; Van de Ven et al., 1976).

For such *in situ* coordination efforts to enhance team performance, individuals must be motivated on some level to pursue team goals. They must also accurately determine what they should do to help the team. The first requirement is generally a fair assumption in a team given that teams are defined by the shared nature of their goals (Griffin, Somaraju, Dishop, et al., 2022; Mathieu et al., 2017). Researchers have repeatedly demonstrated the importance of having shared values and goals that team members internalize (Bono & Judge, 2004; DeShon et al., 2004; R. E. Johnson & Chang, 2006). Without a highly shared goal, a team (or group), is unlikely to successfully coordinate. The degree of harmony within team goals can thus be understood as a key requirement for coordination efforts to positively impact team performance.

The second assumption here is that individuals can adjust the tasks and behaviors they engage in to effectively improve team performance. This is not necessarily true in every team and highlights the essential nature of shared mental models or transactive memory systems in the coordination process. Teams that have not developed effective mental representations of work processes cannot effectively coordinate. No matter how aware an individual is of their teammates' actions, they will not be able to act in a coordinated way – managing interdependencies – unless they have a clear concept (i.e., mental model) of those interdependencies. This is because even if they perfectly know what their teammate is doing and will do next, they do not necessarily understand how that information fits into the broader team's work processes or how it impacts their own work. The claim here is that some understanding of how your work impacts others is necessary to adjust your work in a non-random way that positively impacts the team (Hollenbeck & Spitzmuller, 2012). In some extreme cases, a bad mental model may even lead to inaccurate attempts to coordinate, causing performance losses.

It is therefore helpful to consider the processes of *in situ* coordination separately from the effectiveness of such coordination. I propose that individuals respond to coordination signals by adjusting their efforts in ways that they believe will better facilitate team performance. This can be thought of as "stimulated effort" because the effort was initiated by some coordination signal stimulus. Such stimulated effort will be in accordance with individually held beliefs and mental models of the work processes. As such, the effectiveness of this coordination will depend on the quality of their mental models.

Mechanism 3: Stimulated Effort. *Motivated individuals will adjust the tasks and activities they engage in to better facilitate team pursuit of collective goals as a result of in situ coordination.*

There are three additional signal-focused model mechanisms. First, in conjunction with this mechanism, coordinated actions such as those produced through stimulated effort will be visible to team members in some way. Individuals can actively broadcast what they are doing, making requests and informing others there by explicitly producing coordination signals. Otherwise, they can passively yet visibly act in a coordinated manner. Either way, coordinated actions will produce some level of coordination signal which in turn enables future stimulated effort.

It should be noted that though the process of signal development is theoretically separate from the stimulated effort, they are closely related, and could be described as two outcomes of the same mechanism.

Mechanism 4: *In Situ* Coordination Signal Generation. *Stimulated Effort generates implicit and explicit coordination signals.*

On the other hand, *a priori* effort to establish action plans and assign tasks provides each team member with information regarding how to act in a coordinated manner. Thus, such *a priori* effort generates its own form of coordination signals. This *a priori* signal is not dependent on how much coordination action occurs because it is not generated by the actions of others. Instead, it depends on how effectively team members developed individual-oriented models of their actions during the transition phase. For example, team planning, practice, and rehearsal are all tools that a team can use to effectively promote coordination *a priori*. Effective *a priori* coordination will establish a baseline level of coordination signal available to each team member.

Mechanism 5: *A Priori* Coordination Signal Generation. *Stimulated Effort generates implicit and explicit coordination signals.*

Lastly, as described in detail previously, coordination signals experience decay or loss. In some work contexts, for instance, team members frequently must pivot from one task to another. In such cases, a request made by a teammate may be completely obsolete in just a few moments. On the other hand, many work contexts are much slower in pace. In a software development context, a request to fix a bug one day is likely still viable the next day or even week. Thus the longevity/decay of coordination signals is directly related to the timescale at which the work context is measured. Volatile work contexts where task demands change from moment to moment have a much higher decay rate. In dynamic systems analysis, this decay rate is often referred to as a loss term.

Mechanism 6: Signal Loss. *Coordination signals decay over time in relationship to the volatility of the work context.*

The Component Characteristics of Social Coordination

Having discussed three core social mechanisms of coordination defined in the CASER model, we are prepared to identify and discuss critical components and characteristics of a team's system that enables it to experience emergent coordination. While without these characteristics coordination may occur, with these characteristics the theory implies a powerful pattern signal exchange among team members, which reinforces the team's ability to coordinate.

The Motivator. The first component is the motivator. The motivator is the answer to questions such as – *Why do individuals engage in the team's work in the first place?* or *What motivates action in the team?* The nature of the motivator driving a team member's effort has dramatic consequences on the team's ability to work together and coordinate. If for example, the motivator is inconsistent either across people or over time, this can cause withdrawal in the form of reduced motivation (Vroom, 1964). The result is that if there is inconsistency in the motivator there will likely be some number of individuals disengaged from the team's work at any given moment. Not only are disengaged individuals less performant (Judge et al., 2017), but they are more likely to shift their effort toward individually identified priorities and thus engage in more "spontaneous effort" rather than "stimulated effort", making the proposed signal reinforced coordination difficult to achieve.

Likewise, motivators are known to have different strengths (Kanfer et al., 2017; Vroom, 1964). Weaker motivation leads to less effort, which in turn leads to both less overall performance and fewer opportunities to coordinate at all. If there is not sufficient motivation a team will be unable to sustain the level of effort required to make coordination possible. Similarly, there are often numerous motivators acting on individuals at any given time. If individually-oriented motivators are stronger than team-oriented motivators, teammates will be more likely to act “spontaneously” rather than waiting for and responding to coordination signals and to produce coordinated “stimulated effort”.

The Team Members. Team members are the next critical component of the team’s system. While there are numerous characteristics of team members that we could discuss, there are two that are particularly important to the emergence of feedback-amplified coordinated action. These are 1) cohesiveness/unity, and 2) stability/readiness.

Both diversity and faultlines have important implications for team cohesion and unity (Choi & Sy, 2010; Flache & Mäs, 2008; Molleman, 2005; Thatcher et al., 2003). In a team, individual differences including experiential, demographic, educational, personality (Lau & Murnighan, 1998; Portes & Vickstrom, 2015), etc. can each have dramatic impacts on the unity and function of a team. The faultline literature provides a deeper theoretical discussion of this concept, considering how observable surface-level diversity often has a large impact on team cohesion early in the team’s development but deeper differences (e.g., personality) have more impact later on (Lau & Murnighan, 1998).

Unity and uniformity lead to greater social identification (Abrams & Hogg, 1999; Stets & Burke, 2000), thereby increasing motivation to act in a prosocial manner. Such effects also increase the desire to interact with, communicate with, and generally increase awareness of others. As such, highly united and uniform teams will often be more efficient at coordination.

These effects do not mean that diverse teams cannot coordinate effectively; diverse teams are often able to coordinate highly effectively. However, there are significant barriers to unified team processes and coordination if a group has significant salient faultlines (Lau & Murnighan, 1998). Various actions and activities have been shown to effectively mitigate or break down the effects of faultiness. For example, research has investigated ways to develop inclusive work cultures (Pless & Maak, 2004) including diversity training practices (Bezrukova et al., 2012) effectively. Similarly, identity and categorization theories suggest efforts to build a clearer team identity, including team-building and -development training, help mitigate the challenges associated with highly diverse teams (Stets & Burke, 2000; J. C. Turner, 2010) and promote unity. Similarly, there is evidence that diversity and allyship programs can improve team identities and performance (Taylor, 2015). In the end, teams with a collective identity will be more aware of, and more responsive to each other's needs, regardless of how this shared identity is formed.

Despite the connections between diversity and team cohesion, when considering uniformity/unity of a team in the context of coordination, sharedness in cognitive models is as important as sharedness in ethno-demographic factors. As DeChurch meta-analytically illuminated (DeChurch & Mesmer-Magnus, 2010b), the quality of one's mental model has a tremendous impact on their ability to coordinate as a team. The more accurate and precise one's mental model, the less information an individual requires when responding to coordination signals (i.e., coordinating *in situ*). While having a shared identity and mitigating challenges due to faultlines may enable team members to communicate more effectively and motivate them to put more effort into *in situ* coordination, a shared understanding of their team's work and tasks is essential for such communication to have positive results. No matter how closely a group identifies with each other or how well they can communicate, it will not make much difference if they have divergent concepts of what the team should be doing and what their own role should be. In fact, without an understanding of how one's efforts impact others, teams that have a strong identity may act in an entirely social manner that enables team members to interact more with each other but does not manage task interdependencies. Thus, establishing shared and accurate mental models is a priority for teams.

A second characteristic of team members that will facilitate emergent coordination is the "stability" of individual motivational states or "readiness". If individuals act as soon as they become aware of a motivational stimulus, they do not have time to be influenced by the actions of others. Unless team members have a period where they are susceptible to the influence of others before determining their next task or action, they will act based on individual preferences (spontaneous effort). Essentially, individuals cannot be too quick to act on their motivation, or individual motivations cannot be too strong. This phenomenon is alluded to in the operations literature and can be referred to as a "ready" state or "readiness" (Cunningham et al., 2002; Wesensten et al., 2005; Wohl, 1966). I claim that a ready state of action, where an individual or component of a system is prepared for its next action but waits for the right impetus or signal, is necessary for the coordination of complex systems. A ready state often overlaps the performance of one's tasks. For example, in an orchestra, a violinist will continue playing their part even while continually readying themselves for input from a conductor or other musicians. The members of an orchestra must know their part well enough that they can both play their part and be ready for signals from the conductor at the same time.

As another example of a ready state, consider the state of an audience following a performance or speech. In many cultures, it is appropriate and even expected to applaud at the end of a performance, yet in some situations, it is not. For instance, it is considered impolite to applaud between movements of a musical piece despite potentially long silent pauses. This leads to a somewhat ambiguous situation for an unaccustomed audience member. In these ambiguous scenarios, untrained audience members are in a ready state, prepared to applaud but unwilling to be the first to applaud in case it is the wrong moment. As has been anecdotally documented by various individuals, it is easy in such situations to start an entire audience applauding (Díaz-Agea et al., 2022; Freedman et al., 1980); one person simply needs to start clapping loud enough to be heard to cause cascading applause (Díaz-Agea et al., 2022). In fact, in a social-motivational process, such moments of applause can motivate members of an audience that otherwise would have been completely uninclined to applaud at the given moment to start clapping. In this way, the actions of others can serve as the motivator, stimulating individuals to action, not just the guidepost directing that action.

One consequence of the need for readiness is that in high-stakes and time-dependent scenarios, teams have more constrained ready time and thereby are more susceptible to coordination errors (Carron et al., 2002; Golden et al., 2018; Macnamara et al., 2014; Van Fossen et al., 2021). In such situations, individuals are driven to perform their tasks quickly, which limits their ability to be responsive to their teammates. Countering this requires significant effort. Again, an orchestra illustrates this point well. Music is highly time-dependent and if one member of the team is even a fraction of a second off in their timing, it will be noticeable. Coordination under such conditions requires tremendous amounts of precise rehearsal so that each member of the orchestra knows exactly their role in the ensemble and how it relates to everyone else's parts. This reflects significant transition phase coordination aimed at developing both individual and relational aspects of mental models. This enables members of an ensemble to perform their tasks while maintaining a ready state, responding to coordination signals around them.

Depending on the nature of work, and the experience of the team, stimulated effort will require a different level of readiness, but in every case, unless members of the team are sufficiently ready to respond to each other, stimulated effort will be inhibited to some extent. Readiness can be promoted by making one's tasks easier, thereby allowing individuals to spend more effort preparing to respond to coordination signals. This can be achieved through deliberate practice, or through strategies to simplify and aid the performance of individual tasks. Alternatively, readiness can be promoted by deliberately pausing or slowing initial performance to allow individuals to be responsive. In either case, the ability of a team to maintain ready states is an essential factor in enabling emergent coordination.

Teams Work Context. A team's work context has significant implications on the nature of coordination in a team. Specifically, the context is critical to producing a pattern of feedback-amplified coordination. The visibility and availability of a coordination signal are significantly impacted by the work context. In some work contexts, individuals primarily work alone. In modern team contexts, teams may primarily work with each other virtually. These situations make it difficult for team members to be exposed to coordination cues and signals *in situ*. Other work contexts have established procedures, cultural norms, and spaces that are explicitly designed to make team efforts visible to other members of the team (Weick, 1993). For example, the agile working process used by many software development teams enables team members to easily identify what other members of their team are working on and the interdependencies between their work (Abrahamsson et al., 2017; Dybå & Dingsøyr, 2008). Additionally, the work context can make *a priori* forms of coordination more easily accessible (e.g., visible reminders of action plans) further supporting the team's coordination efforts. Although we do not fully understand the importance or impact of such factors, researchers have demonstrated that context impacts the effectiveness of coordination (DeChurch & Mesmer-Magnus, 2010b).

Additionally, work contexts can be well designed to support the team working in unity. Culture (Carvalho, 2017), organizational policy, and physical spaces have tremendous potential to impact team coordination efforts, but relatively little research has been done in this space (Carvalho, 2017; DeChurch & Mesmer-Magnus, 2010b; A. Espinosa et al., 2002; V. I. Espinosa et al., 2022). More studies on the contextual factors that facilitate team development are direly needed. For example, factors such as the communication constraints of tasks are expected to impact performance (Katz & Tushman, 1979). If tasks are expected to be completed too quickly it can have negative impacts on quality, while too much time leads to periods of inactivity. As a related note, part of the additional work context factors that may impact a team's ability to coordinate effectively would include the timing of feedback from others' work efforts being precisely when one is most susceptible to the given signal. If this is possible, it has clear potential to positively impact team science. For the time being, it is sufficient to note that the work context can have an essential impact on these processes.

Formalization of the CASER Model

To this point, I have presented the CASER model as a narrative description of mechanisms and components of a team that impact its ability to coordinate. Building on this I now develop the formalization of the CASER model in a dynamic systems framework (Matusik et al., 2019; Strogatz, 2015).

Table 1

Mathematical Notation Used in the Formalized CASER Model

Value	Symbol	ND Symbol	Role	Description
Ready State	R	$\rho = \frac{R}{R_c}$	Stock	The number of motivated individuals ready to act.
Coordination Signal	S	$\gamma = \frac{S}{S_c}$	Stock	How much coordination signal there is available to team members.
Work	W	$\omega = \frac{W}{W_c}$	Stock	How much work is done. Performance is defined here as the change in work over time.
Time	t	$\tau = \frac{t}{t_c}$	Time	Represents a unit passage of time.
Social Responsiveness	k	$k^* = \frac{m}{l_R^2}k$	IV	To what extent individuals respond to the coordination signals they are exposed to. This is closely related to *in situ* coordination.
Plan Precision	p	$p^* = \frac{p}{m}$	IV	How much coordination signal is available due to *a priori* coordination.
Motivational Strength	m	–	Model Parameter	How motivated members of the team are to act.
Signal Loss	l_S	$r_l = \frac{l_S}{l_R}$	Loss Parameter	How quickly coordination signal decays in the system.
Ready State Loss	l_R	–	Loss Parameter	How quickly motivated individuals tend to act in the absence of coordination signal (i.e., spontaneous effort).
Interdependence Constant	β_C	$r_\beta = \frac{\beta_C}{\beta_U}$	Outcome Parameter	To what extent coordinated (stimulated) effort leads to performance.
Independence Constant	β_U	–	Outcome Parameter	To what extent uncoordinated (spontaneous) efforts lead to performance.

Note. ND stands for nondimensionalized symbols. The Motivator Strength m, Ready State Loss l_R, and Independence Constant β_U are all treated as model constants with the characteristic values and removed from the non-dimensional equations.

The Model

Dynamic systems models (DSM) are often represented by stocks and flows. Variables that represent quantities, levels, or magnitudes are referred to as "stocks". The relationships between these stocks are referred to as "flows". In these terms, a DSM enables us to account for the temporal changes in a system over time.

We can think of a team's work system in terms of the amount of work done that is coordinated and the amount that is not. Due to interdependence, we can further assume that coordinated effort leads to greater performance (DeChurch & Mesmer-Magnus, 2010b) than uncoordinated effort, but is subject to some level of process loss (due to the effort required to shift to a more coordinated action). At a team level, we can describe a relatively simple system building on these concepts. There are three system stocks or variables of interest. These are the number of individuals in a motivated, ready state (referred to as R in the equations below), the amount of coordination signal present (referred to as S in the equations below), and the total amount of work done. As a DSM, the formalized CASER model will include three differential equations, one describing the change in each stock (see Equations 1, 2, and 3).

The flows of the model come directly from the theoretical mechanisms developed previously. First, there is some motivator that increases the overall level of team readiness to act. I will label a parameter for the motivational strength m in the equations below. This is the theoretical "Mechanism 1" described above. The stronger the motivation for team members, the stronger the m value will be.

Next, there are two flows out of the ready state stock. The first is from uncoordinated effort, or *spontaneous effort* (i.e., Mechanism 2 described above). The prominence of spontaneous effort is largely dictated by the stability of the ready state. If team members have a highly stable ready state, there is more opportunity for them to respond to external coordination signals and perform in a coordinated manner. Therefore, the spontaneous effort mechanism is controlled by a parameter, l_R, representing the *loss* (i.e., instability) of the ready state. Under time pressure, when it is difficult to wait for or respond to coordination signals – or when a task is too complicated to maintain a responsive ready state while performing tasks – the ready state will be less stable, spontaneous effort will be more prevalent, and the l_R parameter will be larger.

Next, there is a *stimulated effort* (i.e., Mechanism 3) mechanism flow. This flow represents a loss in the number of individuals in a ready state, but an increase in the total coordination action performed. Due to *in situ signal generation* (i.e., Mechanism 4) this will lead to a corresponding increase in coordination signal; the more coordinated effort, the more information there will be on how to best coordinate. Unlike spontaneous effort, this is responsive to coordination signals (the higher the level of the *S* stock, the more stimulated effort should be expected). The concept is that when an individual in a ready state is exposed to the performance of others (i.e., they have the information required to act in a coordinated manner), they will be able to adjust their efforts and perform coordinated actions. This mechanism requires individuals who are in a ready state to interact with the coordinated performance signals of others and is therefore mathematically represented as the product of the ready state stock and the coordination signal stock. This is further controlled by a single parameter, *k* (for *coupling* strength or social responsiveness), which theoretically represents the responsiveness of individuals to each other. Individuals that have relation-oriented shared mental models care about shared outcomes, and who are in a context where communication is easy will have a strong coupling strength. In contexts where communication is sparse (e.g., virtual teams), communication is difficult, or social divides prevail, we would expect a weaker coupling and lower value for *k*.

Coordination signal has its own direct source based on *a priori* coordination efforts (i.e., Mechanism 5). The more the team plans and prepares during the transition phase for specific action plans, the more information (i.e., signal) individual team members will have regarding how to act in a coordinated way. This in turn will augment the total amount of stimulated effort. This is represented by p in Equation 2 below. I refer to p as Plan Precision, although it encompasses other forms of *a priori* coordination efforts broadly.

For the final flow, there is a level of loss in the coordinated signal (i.e., Mechanism 6), representing the inherent volatility/decay of information over time. For example, if someone sees a team member working on a task, that information will become less helpful in efforts to coordinate as the time since the observation progresses. This decay in information is modeled by another loss term in the coordinating signal stock of the system. This is represented as l_S in Equation 2.

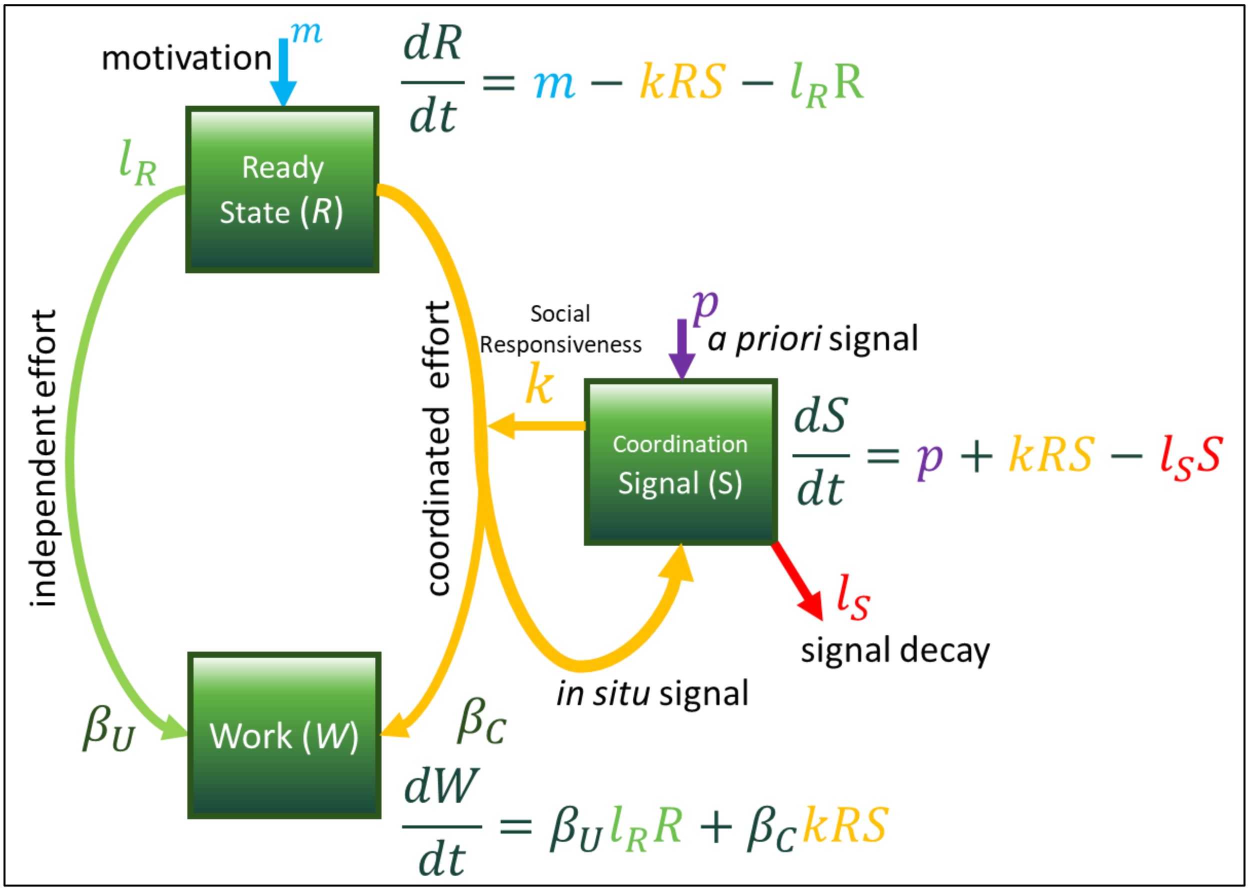
$$\frac{dR}{dt} = m - kRS - l_R R \tag{1}$$

$$\frac{dS}{dt} = p + kRS - l_S S \tag{2}$$

This model is both convenient and nearly isomorphic with the Strogatz (2015) model, making it readily usable. However, there are a few conceptual issues with the model that should be clarified to make it more usable in a team performance context. First, it is valuable to explicitly model the connection of this system with performance. We can define a third stock in the model representing the total work done over time. Consistent with other conceptual definitions of performance, we can specifically define outcome-oriented performance as the change in work accomplished in a given time period. We will refer to work notationally as W. Work accomplished is a function of the amount of coordinated effort, (i.e., it is proportional

Figure 5

Dynamic Systems Representation of the CASER Model



Note. Boxes represent systems stocks. Arrows represent the flows. The arrows are color-coordinated, corresponding to the elements in the corresponding differential equations.

to kRS), and uncoordinated effort accomplished (i.e., it is proportional to $l_R R$). We can represent the rate at which coordinated and uncoordinated efforts lead to desired outcomes using two parameters: β_C and β_U respectively. The greater β_C and β_U are the more strongly coordinated and uncoordinated efforts (respectively) impact work outcomes. The greater the difference between these two values the more important coordination is. This leads to a third equation:

$$\frac{dW}{dt} = \beta_U l_R R + \beta_C kRS \qquad (3)$$

Analysis of the Formal CASER Model

Following general practice for similar DSMs, I investigated the dynamic behavior of the proposed formal CASER model. This model is simple in nature and most of these steps can be done in closed form. However, the resulting closed-form outcomes are difficult to interpret without applying numerical methods. For the purpose of this dissertation, I characterize this first model to the extent possible without using synthetic simulations.

This CASER model specifically allows us to investigate coordination feedback and the potential for feedback to lead to amplified coordination. Such positive feedback loops are theoretically highly important and have significant implications for team interventions aimed at amplifying coordinated action.

Following general dynamic systems analysis practice, I used a multi-step procedure for characterizing the behavior of the CASER model's dynamic system. I first generated a non-dimensional representation of the model (this is presented in Appendix A). This allows us to consider the general pattern of dynamic behavior implied by the model without worrying about scale or units (Strogatz, 2015). Next, I investigated the nature of equilibrium and potential bifurcations in the model and discuss their implications. I then discuss the trajectories and phase portraits of the system.

Steady State and Equilibrium Analysis

With a dimensionless system defined (See Appendix B), we can explore the qualitative behavior of the system and how it is expected to respond to different interventions. First, we will evaluate the null clines and steady states of the system. The null clines for the system are found by setting the differential equations to 0 and solving. We will ignore any potential nullclines for the work equation[1]. This leaves us with the following null clines:

$$\rho = \frac{1}{1+\gamma} \tag{4}$$

$$\gamma = \frac{k^{\star}p^{\star}}{r_l - k^{\star}\rho} \tag{5}$$

By construction, this equation for γ's null cline strictly assumes that $p^{\star} \neq 0$. When $p^{\star} = 0$ (as is the case when there is no spontaneous effort) the null clines for the $\frac{d\gamma}{d\tau}$ equation split into two cases.

$$p^{\star} = 0 \Rightarrow \gamma = 0 \ or \ \rho = \frac{r_l}{k^{\star}}$$

The nullclines are presented in Figure 6 below. For ρ, the single possible null cline is not dependent on any parameters (i.e., we have defined the nondimensional system in a way that has removed all non-unitary parameters from the equation for the ready state), and therefore there is only one line for the γ null cline below. This is indicated by the double black line. Although the gamma null cline depends on three parameters, this can be further simplified to two parameters: $p^{\star}$ and $\frac{r_l}{k^{\star}}$. For reasons which will become clear later, we will define $\tilde{k}$ as the inverse of the second parameters. In the figures below Social Responsiveness is measured in terms of this value.

$$\tilde{k} = \frac{k^{\star}}{r_l}$$

Figure 6 demonstrates the effect of varying both of these parameters. Changes in $p^{\star}$ are indicated by the line type (solid vs. dashed) while changes in $\tilde{k}$ are indicated by the line color.

[1] As assumed, $r_{\beta} > 0 \Rightarrow \frac{d\omega}{d\tau} > 0$

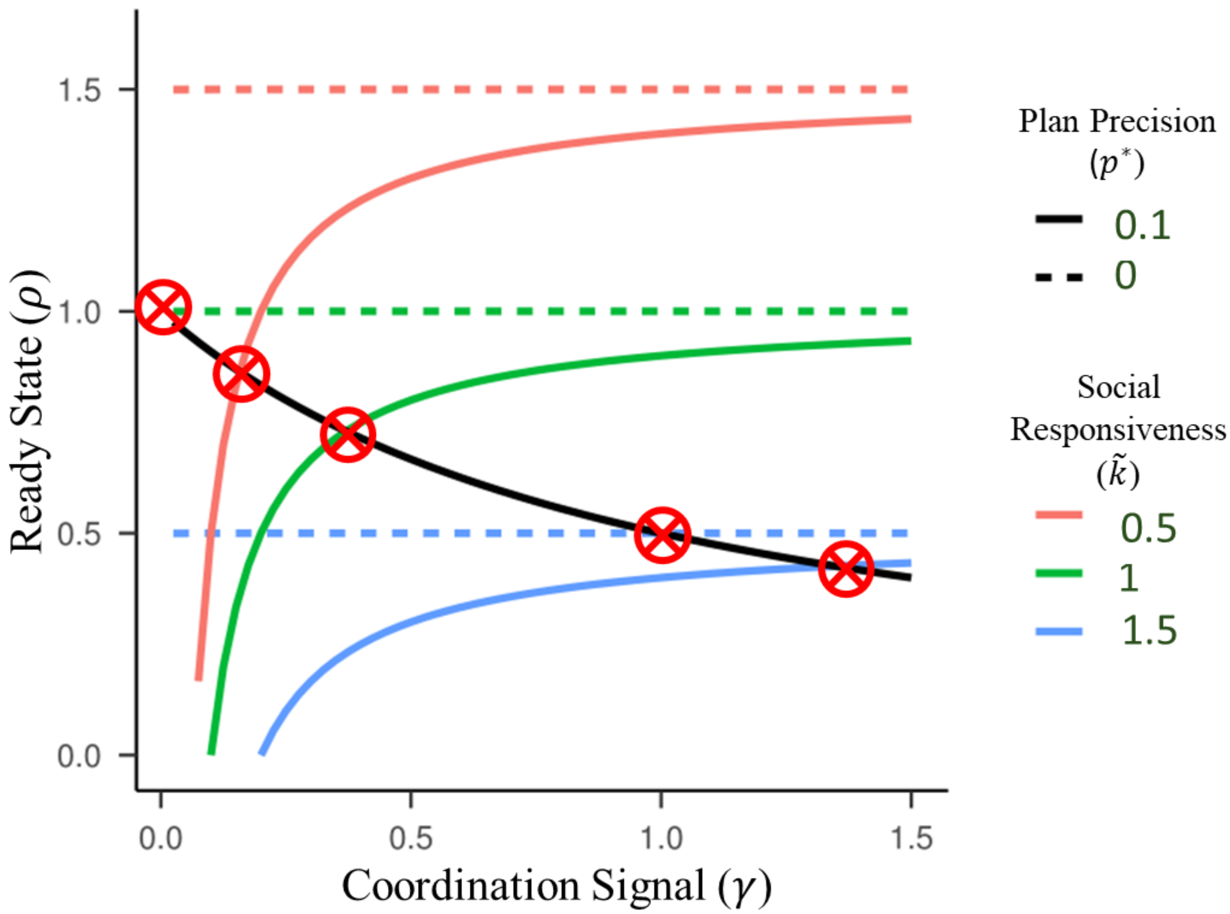
Note that the fixed points are round at the intersections between the colored lines and the double black line.

We see that when $k^\star < r_l$ and $p^\star = 0$ there is no intersection between these null clines, implying that there are no non-trivial fixed points in these cases. We will investigate this further by explicitly solving for the fixed points, showing that in such cases the system will approach a state with $\gamma = 0$. For all other cases, there is a positive intersection between the two null clines. We further note that increasing $\tilde{k}$ decreases the ρ values for the null clines. This will have the effect of increasing the total amount of coordination. This is unsurprising, given that $\tilde{k} = \frac{k^\star}{r_l}$, so larger values of $\tilde{k}$ indicate that there is a higher degree of coupling in the team in comparison to the loss ratio of the system. Intuitively, this should increase the steady state value of γ.

For a given value of h, the null cline for γ asymptotically increases toward a value controlled by the null cline when $p^\star = 0$. The larger $p^\star$ is, the more slowly the null cline approaches this value and consequently, the higher the value of γ at the intersection point between the two null clines. This demonstrates the intuitive fact that increasing the value of $p^\star$ (i.e., the rate of spontaneous effort) should increase the steady-state value of the coordination signal present.

Figure 6

Nullclines For Ready State and Coordination Signal



Note. The solid black line indicates the nullcline for the ready state. This is not dependent on the parameters so there is only one line. The colored lines indicate nullclines for the coordination signal at different levels of social responsiveness ($\tilde{k}$ - indicated by color) and plan precision or *a priori* signal (p^* - indicated by line type) holding all other parameters constant. Intersections (indicated with a red x) indicate steady, fixed points for the given parameters.

Having made these observations, we will now calculate the values of the fixed points explicitly. Setting Equations 7 and 8 to equality and solving reveals the fixed points (ρ, γ). For simplicity, we define $g = (k^\star + k^\star p^\star + r_l)$ and $h = (k^\star + k^\star p^\star - r_l)$:

$$f_1 = \left(\frac{g + \sqrt{g^2 - 4r_l k^\star}}{2k^\star}, \frac{h - \sqrt{h^2 + 4r_l k^\star p^\star}}{2r_l} \right)$$

$$f_2 = \left(\frac{g - \sqrt{g^2 - 4r_l k^\star}}{2k^\star}, \frac{h + \sqrt{h^2 + 4r_l k^\star p^\star}}{2r_l} \right)$$

We can assume $r_l > 0$ (because $l_R > 0$ and $l_S > 0$ by definition), $k^\star > 0$ (because necessarily $l_R > 0$, $m > 0$, and $c > 0$), and $p^\star \geq 0$ (because $p \geq 0$ and $m > 0$). For $p^\star \neq 0$, at f_1 the signal, γ, must be negative, which is not possible. Therefore, there is only one possible fixed point (i.e. f_2) whenever $p^\star > 0$. Similarly letting $p^\star = 0$, if $r_l > k^\star$ the signal must still be negative at f_1. Therefore f_1 is not a viable fixed point whenever $r_l > k^\star$. Otherwise, there are two equilibrium points only when $p^\star = 0$ (i.e., $p = 0$) and $r_l \leq k^\star$. These are found at the points:

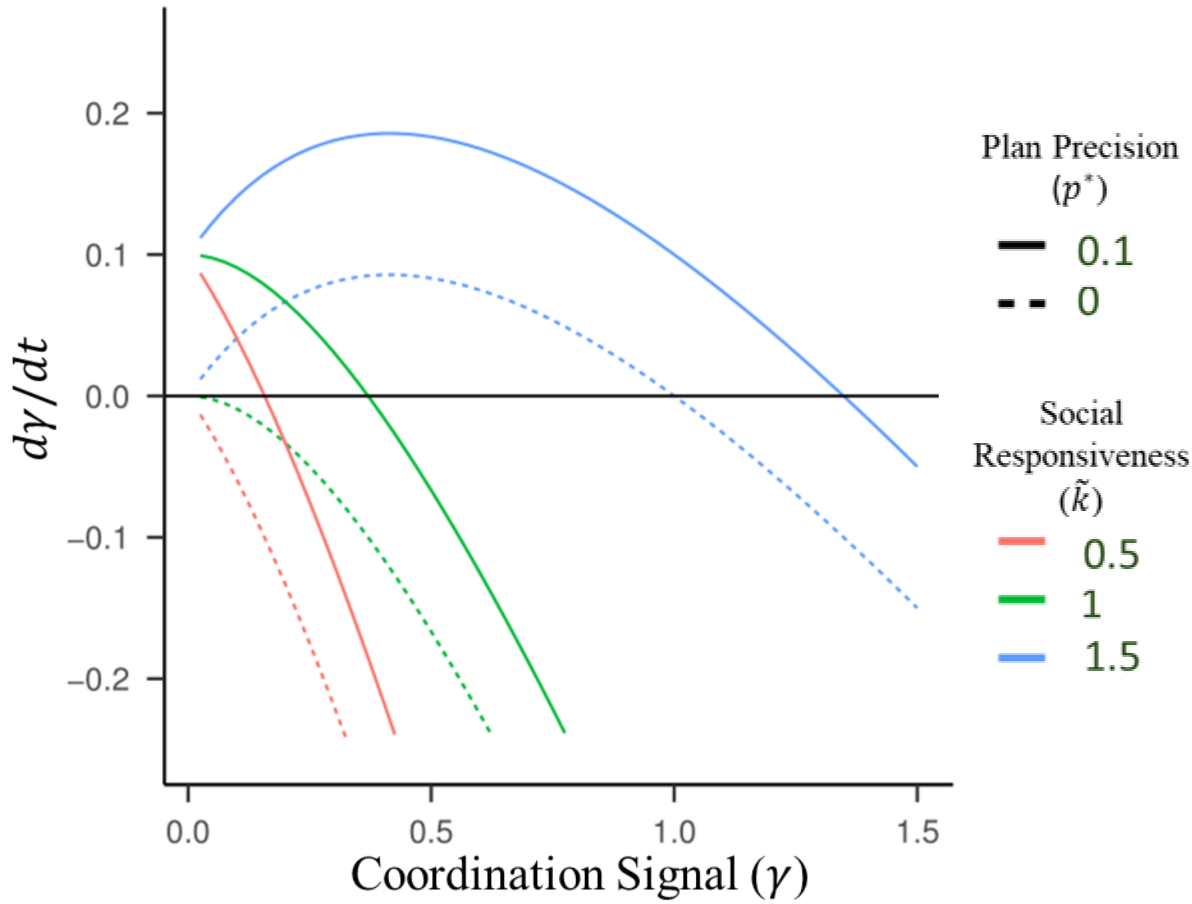
$$f_1 = (1,0)$$

$$f_2 = \left(\frac{r_l}{k^\star}, \frac{k^\star - r_l}{r_l} \right) \tag{9a}$$

In all other cases, the only equilibrium point is given by the original f_2 equation above (Equation 6). For illustrative purposes, we plot the amount of coordination information (γ) against its derivative. Notice that the curve necessarily has a positive vertical intercept (for $p^\star > 0$, and $c^\star > 0$) and making f_2 a stable, fixed point in all cases. Similarly, it is clear that when there are two fixed points, f_1 is unstable. All other potential fix points are at boundary conditions. A quick assessment of boundary conditions (i.e., $\gamma = 0$, and $\rho = 0$) demonstrates that there are no additional boundary-based fixed points.

Figure 7

Phase Portrait for System Coordination Signal



Note. Graph of the phase portrait for the system's coordination signal. Fixed points are indicated by places where the derivative of γ (indicated on the vertical axis) is 0. The fact that all non-zero horizontal intercepts have shifted from positive to negative indicates that all non-zero fixed points are stable.

Fixed points are found where the curves depicted in Figure 7 cross the horizontal axis. To characterize their stability, we can assess the slope of these curves at the intercepts. Negative slopes indicate a stable point, while positive slopes indicate an unstable fixed point. It is straightforward to demonstrate that for γ large enough, the derivative of γ is necessarily negative in all cases. Thus, the largest fixed point is necessarily stable. In the specific case where there are two fixed points, it is straightforward to show that between the two points, the derivative is positive, so f_1, the lower of the two fixed points, is necessarily unstable.

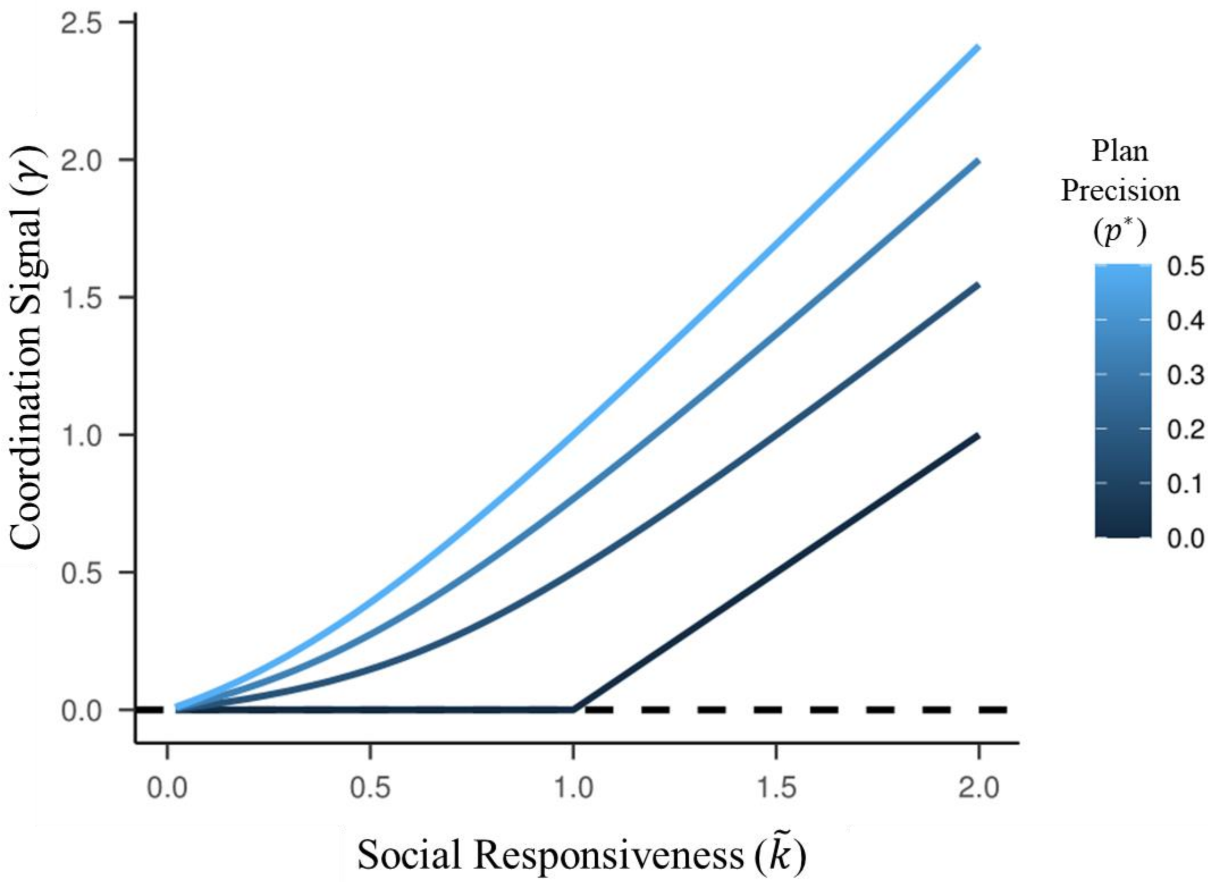
Lastly, in Figure 8, I graph the fixed points for various values of $p^\star$ and $\frac{k^\star}{r_l}$.

The fixed point's value appears to increase exponentially as $\tilde{k}$ increases, until it reaches a given linear rate of growth after which it continues to grow linearly. The larger the team's rate of spontaneous effort (i.e. $\tilde{k}$), the faster the fixed point's asymptotic linear growth. Notice that there is only a bifurcation when $p^\star = 0$. In this case, the single fixed point remains stable at the $\gamma = 0$ until $\tilde{k} > 1$ (i.e., $k^\star > r_l$) portion, at which point there is a bifurcation. $\gamma = 0$ remains an unstable, fixed point while there is a fixed point that increases in magnitude linearly with respect to $\frac{k^\star}{r_l}$.

Conceptually, when there is no spontaneous effort, a lack of coordination is a fixed point. But as long as the coupling strength is great enough, any perturbation (perhaps in the form of coordinated action) will lead the system to jump to a stable coordinated state. Any level of spontaneous effort eliminates this bifurcation behavior.

Figure 8

Steady State Coordination Signal vs. Coupling Strength



Note. Dashed black line indicates unstable, fixed point at no coordination when $p^*=0$. This is the only bifurcation.

Performance in the CASER Model

We will now make a quick note regarding coordination and performance. Performance can be thought of as the change in work over time, and so we set:

$$\text{performance} = \frac{d\omega}{d\tau}$$

In this model, interdependence is represented in the ratio r_β. Setting this to 1 simulates a system where there is no difference between the impact of coordinated and un-coordinated effort of desired outcomes. There is no benefit and no additional loss due to process costs for coordinated work. Thus, uncoordinated and coordinated effort are essentially indistinguishable when $r_\beta = 1$. This is characteristic of complete independence (i.e., one team member's work does not impact another's). This motivates Lemma 1:

|**Lemma 1:** *Whenever coordination occurs (i.e., $\gamma > 0$), nondimensionalized performance is unitary if and only if the system is operationally independent (i.e., $\frac{d\omega}{d\tau} = 1 \Leftrightarrow \beta_U = \beta_C$)*

Proof: All fixed points are along the null clines for ρ, so at the fixed point(s) we have:

$$\rho = \frac{1}{1+\gamma} \Rightarrow \frac{d\omega}{d\tau} = \frac{1 + r_\beta \gamma}{1+\gamma}$$

$$\gamma \neq 0, r_\beta = 1 \Leftrightarrow \frac{d\omega}{d\tau} = 1$$

Note that at $\gamma = 0$ all work is done in an uncoordinated manner and performance is still equal to 1.

Conveniently (i.e., by design), the given nondimensional arrangement of the system has independent performance set to a constant value of 1. Any performance value greater than 1 in this nondimensional team performance system represents an amplification of performance by means of interdependence.

Summary

Up to this point, my dissertation develops the Coordination Signal Theory (CST) – a theoretical framework for understanding a synergistic amplification of team coordination. Building on this framework, I have developed a theoretical model for how socially-driven feedback may function in a team coordination context at the team level. This model is referred to as the CASER model. Below are the principles implied by this model.

Principles of the Model

Using the tools of dynamic systems analysis, I have identified various qualitative patterns that the proposed CASER system will follow. These qualitative patterns are used to highlight principles of interest implied by the formal theory. First, I have demonstrated that the theoretical model is expected to have stable equilibrium trajectories. From a practical, or theoretical, perspective as long as the way in which a team's system functions (including the typical level of motivation, team coupling, and stability of both ready states and information) is fairly static compared to the actual effort and performance of team members I propose that there will be a dynamic trajectory for the team's level of coordination where it approaches some stable level. This is important because when considering the system in the long term we can characterize it simply in terms of these stable equilibrium values. On the other hand, when characterizing the short-run dynamics of the system, these theoretical mechanisms imply that whatever the current level of coordination is, it will gradually and smoothly get closer to this equilibrium value. This is driven by a process of dynamic coordination feedback.

Equilibrium or steady-state levels of coordination are likely more important than temporary episodes of highly coordinated action. This is a principle of dynamics; often systems that are much weaker, but consistent, have a greater impact in the long run than those with very short bouts of strength. Recognizing the theoretical existence of such equilibrium behavior, and characterizing its nature is therefore of significant practical and theoretical importance.

Principle 1: *Coordination in a team will generally follow a dynamic equilibrium trajectory, approaching some steady level of coordination within a team.*

Notably, the steady equilibrium described by this system is 0 whenever both 1) the team has no external source of coordination, and 2) the rate of decay for the coordination signal's information is high compared to the coupling strength (i.e., the signal dissipates faster than it can be generated). Whenever there are no external sources of signal that can promote coordinated behavior or external factors promoting coordination, the signal must be steady enough (not decay too fast) to maintain itself. Otherwise, any observed level of coordination will quickly dissipate, and individuals will act almost exclusively in an independent manner. Conversely, when coupling strength is weak compared to the decay rate of information, there must be an external source of coordination information or opportunities for individuals. Otherwise, the team will not have access to the information needed to coordinate.

Many team contexts impose barriers to communication. For example, virtual teamwork environments make it more difficult for individuals to observe and act on cues from their teammates. Similarly, some team contexts can make it difficult for individuals to be influenced or responsive to each other.

This highlights two factors related to a team's coupling strength. The availability of coordination signal and the responsiveness to such signals. The transformation from coordinated effort to coordination signal is an important factor driving a team's coordination. While not discussed at length, the model allows us to consider the impact of the generation of coordination signals. The efficiency of transitioning coordinated effort into coordination signal will have a huge impact on the team's ability to generate enough momentum to establish a steady level of coordination.

In effect, this represents the visibility of others' work in a team. Teams that actively promote and celebrate the efforts of their teammates will be much more efficient at generating coordinating signals from their effort. By contrast, teams that have very independent cultures, or that work in contexts that are separate (i.e. virtual teams), siloed, or solitary will be much less efficient at generating such signals.

Similarly, some team environments make it difficult for individuals to be influenced or responsive to each other, even if there is enough signal. In such cases, team members may be aware of each other but unwilling to, or uninterested in, acting on that information. Teams that lack a clear social identity may be less able to influence each other. In other cases, it may be much more difficult to change one's current task once started, making it hard for team members to be very responsive to each other.

The formal model indicates that in such cases where team "coupling" is weak (either for lack of signal production or lack of responsiveness), the team must rely on external cues and sources of information to act in a coordinated manner. In such cases, without such external cues, it is unlikely, if not impossible, to maintain a coordinated approach to work. Without either a sufficient level of coupling or external forces driving coordination, the team will fail to establish a steady level of coordinated effort.

Principle 2: *When a team establishes a strong level of coupling (i.e., social responsiveness - effectively generates signals and cues regarding each other's activities, and actively responds to these signals) relative to the decay rate of information, the team will exhibit a non-trivial, steady level of coordination. The greater the coupling, the larger the steady level of coordination in the team.*

Principle 3: *Teams exposed to some form of external coordination cues, or that have some inherent force driving coordination, in the absence of* in situ *cues will exhibit a non-trivial, steady level of coordination. The stronger such external influences, the larger the steady level of coordination will be.*

Additionally, the model demonstrates the importance of the relative relationship between the level of instability for the ready state and the stability of coordination information. This ratio directly impacts the possible equilibrium levels of coordination in a team. In particular, by holding the level of stability in the ready state constant, increased stability in coordination information will lead to greater levels of coordination. Generally, the model suggests that the greater the ratio of stability in coordination information to the stability of the ready state, the greater the steady level of performance.

These are concepts that, to my knowledge, have never been discussed or investigated. However, this framework would suggest that this ratio of stability is critical for predicting (and manipulating) team coordination levels. To form a highly coordinated pattern of effort, a team must have some level of stability in a "ready state" such that they can receive and respond to coordination signals. The dimensional representation of a team's performance is used with the stability of the steady state to define the passage of time and is therefore ill-suited to investigating the impact of the stability of the ready state. Future work will need to investigate the impact of the stability of the steady state more fully. However, this work clearly provides evidence for the need to promote, visualize, celebrate, etc. the work done by others to establish an environment well-suited for incubating coordinated effort.

Principle 4: *By holding the stability of the ready state constant, a team's steady level of coordination will be augmented as the stability of coordination information and signal is increased.*

This model also speaks directly to the relationship between coordination, interdependence, and performance. Specifically, coordination does not impact performance at all unless there is a sufficient level of interdependence. However, in highly interdependent teams, coordination may be a critical factor driving the team's performance.

The connection between coordination and team performance is not new. Furthermore, the fact that this relationship is moderated by interdependence is not new. However, this model and its framework more broadly clarify and give important details to these relationships. From the operational paradigm used to establish this model, we see that at least one form of interdependence in this system is defined by the ratio of effectiveness of coordinated effort as compared to the effectiveness of uncoordinated effort. This definition itself is a clarification to the interdependence literature. It bespeaks a way of clarifying task interdependence in an operationally relevant way. In combination with its connection to the impact of coordination, it provides clarity and depth to our understanding of this relationship.

Furthermore, this model can help us to identify potential limitations to our understanding of the impact that interdependence has on performance. Researchers have occasionally failed to find a significant moderating effect of interdependence on the relationship between coordination and performance (DeChurch & Mesmer-Magnus, 2010b). While surprising, these counter-intuitive results could be explained by a lack of clarity in the constructs for coordination, performance, and interdependence. This model provides clarity to all three by situating itself in an operational paradigm. Additionally, the model describes variables that may obfuscate the generally straightforward moderation relationship. Specifically, process losses due to coordination (i.e., the loss of performance due to the effort required to adjust one's work to be done in a coordinated manner) is an explanation for null moderation results. Specifically, if there is a high degree of process loss, interdependence as defined above (the ratio of effectiveness of coordinated to uncoordinated effort) will appear to be much smaller than it would otherwise be.

Principle 5: *Coordination will generally lead to increased performance. This is dependent on the level of interdependence of the team (more interdependence means stronger relationships between coordination and performance), and the process inefficiencies associated with coordination.*

Finally, I note the essential role of feedback in these observed principles. Feedback originating from coordination signals drives future coordination. This feedback is essential to the equilibrium behavior of the system. In fact, much of the behavior described by Principles 1, 2, 4 and 5 are directly related to the existence and nature of feedback in the system. Feedback is driven by the production of coordination information that is then used to signal future coordination in the team. This depends on the coupling strength (See Mechanism 2), the efficiency of generating coordination signal (See Mechanism 4) and the stability of coordination signal (See Mechanism 5).

The notions of feedback and its relationship to a system's ability to stabilize and control itself are well established in various academic literatures. However, this concept of stabilization through feedback is new to the coordination literature. This is a severe limitation of coordination as it restricts coordination to a static emergent state or team process, without acknowledging the complex reality of the dynamics of coordination. The presence of such coordination feedback further highlights the potential ability to augment coordination via means novel to the organizational literature, such as coupling strength (signal generation or responsiveness).

Principle 6: *Feedback is an essential driver of the impact of coordination, and a determinant of a team's ability to establish a steady amplified level of coordinated effort.*

Limitations of the CASER Model

The CASER model presented here is limited in numerous ways. First, it is a simplification of reality. The model takes a very complex phenomenon and simplifies it into a concise system of three equations. While this is reasonable and consistent with best modeling practices (Olenick et al., 2022; Vancouver & Weinhardt, 2012), it does mean that the results are necessarily approximations. This is not an issue, because the model is being used primarily to investigate general patterns implied by the framework developed in this dissertation. However, because it is a simplification and because most of the interpretation was based on the nondimensionalized model, the results of this analysis should be taken as qualitative evidence used to produce principles that are logically consistent with the theory.

These are not quantitative estimations of a parameter or an evaluation of empirical work. This work should be considered a process for generating theory; theory that is logically consistent, theoretically precise, and robust, but still theory, not empirical evidence that anything stated here should be expected in the real world. There is empirical evidence consistent with this model to the extent to which the theoretical concepts used to develop this formal model are supported by their own empirical evidence, but before using this work to guide interventions, make predictions, or make decisions, it should be thoroughly tested empirically for its ability to accurately and consistently predict patterns found in observed data.

Another significant limitation of the CASER model is its reliance on team-level aggregations. The ready state of the team represents some complex pool of the overall readiness to perform across the entire team. While conceptually this may make sense, practically it is a difficult variable to measure or use. The aggregated "coordination signal" variable is similarly problematic. Of particular interest to me is that many of the relationships, process mechanisms, and parameters described by this model may be better represented on an individual and dyadic level. For example, the responsiveness described by coupling strength will almost certainly be different between two people that get along and two people that don't. On the other hand, the ability to observe coordination cues from team members is likely not constant across the entire team. Some team members will be better situated to observe such cues than others. These individual differences and the localized embeddedness of the coordination process mechanisms are important factors that we will investigate in greater detail in the following chapter.

Network Model of Emergent Coordination

It is the long history of humankind (and animal kind, too) that those who learned to collaborate and improvise most effectively have prevailed.

— Charles Darwin

The formal CASER model presented in the previous chapter provides a proof of concept that coordination can produce self-amplifying patterns of spontaneous effort. This work highlighted the impact and importance of feedback loops and signal exchange. By contrast, the present model provides more insight into the emergent multi-level nature of coordination as well as the impact of various forms of interdependence on coordination. The CASER model presented an aggregated approximation of team-level motivation, coordination, and coordination signals. To understand these processes and the implications of this theory more fully, I present this second formalization of this theory which presents a network-based representation of dyadic social coordination signals and influences and accounts for complex interdependence structures. I refer to this second model as the Coordination Signal Network (CSN) model.

The CSN model builds upon the same three mechanisms described by the CASER model – the processes of motivational internalization, spontaneous effort, and stimulated effort. Yet this model provides more depth to this investigation, which allows us to investigate the potential differential impact of *a priori* vs. *in situ* coordination efforts, in team contexts that vary in their level of volatility and complexity. As such, this model enables us to fully investigate the theoretical claims made previously.

By taking a network-based approach, the CSN enables us to consider individual psychological processes and the differences in the broader context of team coordination efforts. This model enables us to more fully recognize and account for the complexity of social structures and interdependence within a team and loosely builds upon the foundational Kuramoto Model (KM) as a model used to understand spontaneous synchronization in various systems.

In this chapter, as in the previous one, I begin by providing a brief overview of the complete CSN model before providing a step-by-step derivation of the model and its background. As noted, this model builds on the same mechanisms as the previous model and thus this chapter does not provide as much theoretical background. After presenting the derivation of the model, I discuss and present a simulation study aimed at investigating the implications of the model and specifically designed to consider the proposed theoretical relationships between *a priori/in situ* coordination efforts and team contextual volatility/complexity.

Overview of the CSN Model

Before deriving the complete formal network-level coordination model I will briefly provide an overview of the CSN. First, I provide an overview of the general system to be modeled, then discuss the moralized mechanisms of the model.

It is assumed that a team is made up of some number of individuals (agents) who will perform some set of tasks. For simplicity's sake, there is a limited number of distinct tasks that the team members can perform at any point. Tasks are interdependent such that the concurrent performance of some task pairs is beneficial while it is best to avoid performing other pairs of tasks at the same time. At every given moment, each team member probabilistically elects to perform one of the possible tasks. The aim of the model is to evaluate those mechanisms that enable a team to coordinate task performance and adaptively manage task interdependence.

The number of team members is defined as n. Similarly, the number of possible tasks is defined as m. The model is made up of an equation dictating the probabilistic task that individual team members will perform at any given time. Specifically, $x_{i,[t]}$ is defined as an *m*-dimensional vector encoding the probability of team member *i* performing each of the given tasks at time *t*. The basic architecture of the model is that the probability of team member *i* performing each of the tasks is based on some discrete Markov-like transition.

$$x_i(t+1) = Mx_i(t) \, ,$$

where *M* is an *m*-by-*m* matrix. If formalize the mechanisms and theory described previously to meaningfully define *M* such that it accounts for psychosocial patterns of coordination.

The transition matrix, *M*, referenced in Equation 7 is defined by the column-normalized Hadamard-product (i.e., element-wise product) of three matrices. The first matrix represents individual objectives and preferences. This is closely related to the mechanism of *spontaneous effort*. Mathematically this matrix is written as Ω. The second matrix represents the impact of *in situ* coordination and is written as *V*. The third matrix describes the impact of *a priori* coordination. This is represented as *P* in the equations below. After being multiplied together, the columns are normalized so as to ensure that the resulting matrix is a Markov matrix. This normalization is represented by traditional matrix multiplication on the right by an appropriate diagonal matrix – represented here as *D*:

$$M = (P \odot V \odot \Omega)D$$

$$\Rightarrow x_i(t+1) = (P \odot V \odot \Omega)D \, x_i(t)$$

In the remainder of this chapter, I derive the CSN model, providing theoretical, mathematical, and numerical evidence for the model before presenting a simulation study used to investigate this model.

Deriving the CSN Model from the Kuramoto Synchronization Model

The foundation of this work is the spontaneous synchronization model laid out by Kuramoto (1984). The Kuramoto Model (KM) provides a mathematical representation of the mechanisms through which various physical, biological, social, and psychological phenomena may occur. For example, the same model has been used to describe the emergent synchronization of clocks and pendulums, synchronized applause, and firefly blinks. I propose that synchronization provides a useful lens from which to understand the potential mechanisms driving the emergence of coordinated action in a team. For example, in a rowing team where each individual is performing essentially the same oscillatory task and motivated to do it at the same time, we could model their performance using the KM.

I note that while synchronization implies performing the same task at the same time, coordination is much broader than this. Specifically, coordination implies performing the right task at the right time *given what others are doing*. Despite the differences in synchronization and coordination, I will demonstrate that the KM provides a powerful foundation from which to build a mathematical understanding of coordination. I extend the KM (continuous in time, continuous in space, and implies synchronized action) to a general form that is discrete in time, discrete in space (i.e., network-based), and applies to both synchronization and coordination more generally.

Mathematically the KM is defined for a set A of n "nearly identical" oscillators. $A = \{a_1, a_2, \dots, a_n\}$. Each oscillator is defined as being very near a shared limit cycle, the state of each oscillator is indicated based on its position within the limit cycle represented as θ. The KM is as follows:

$$\frac{d\theta_i}{dt} = \omega_i + \frac{k}{n}\sum_j \sin\left(\theta_j - \theta_i\right) \tag{8}$$

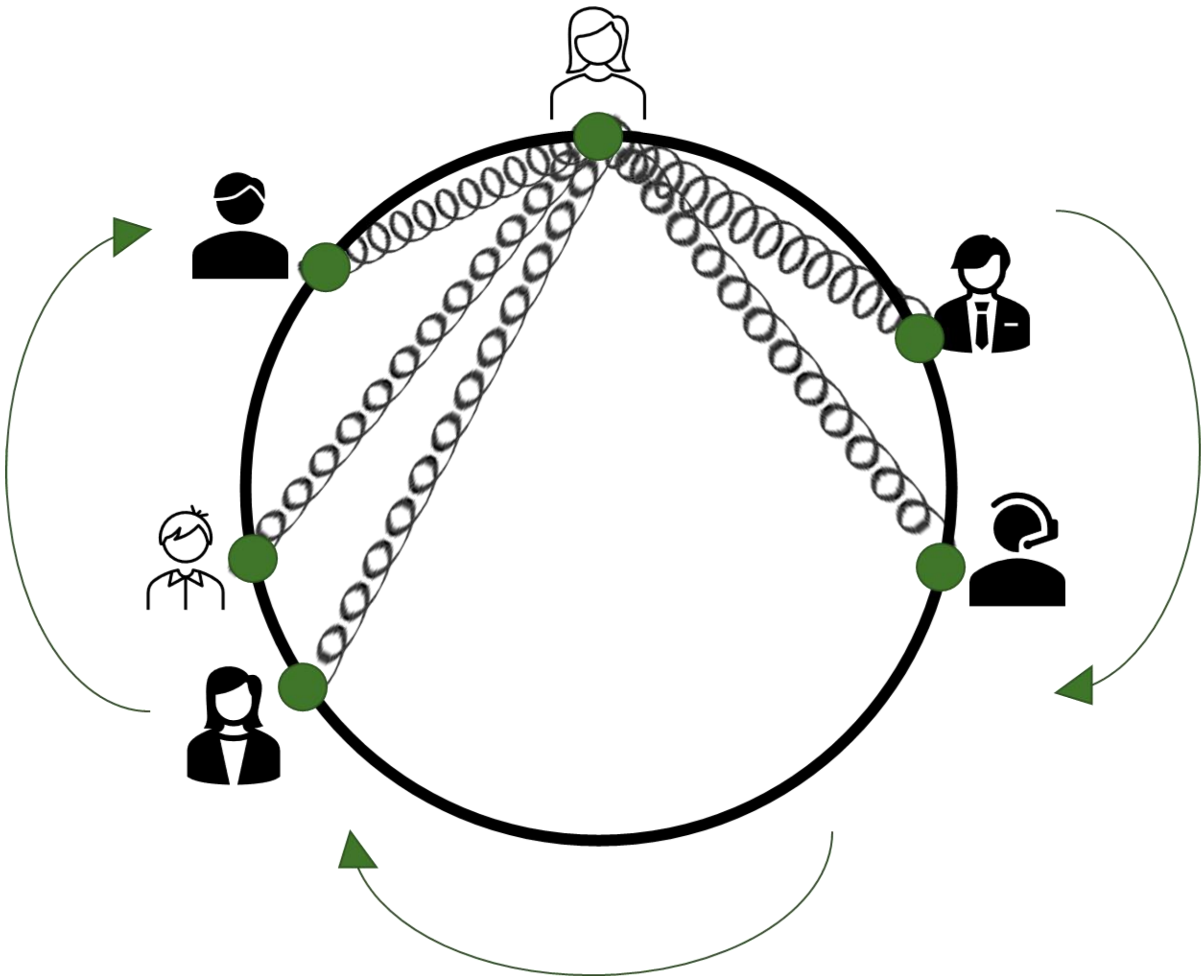
A complete review of the KM is beyond the scope of this dissertation. The main concept is that each oscillator is influenced by the other oscillator. This model is conceptually equivalent to a system of n massless beads on a frictionless ring that each has a natural frequency $\omega_i: i \in \{1,2, \dots, n\}$ dictating a natural rate of rotation. Each bead is then connected by a spring with spring constant k.

Each oscillator is influenced to be as near the other oscillators as possible while being influenced by its internal rate of rotation. This model has been used to describe various synchronization processes found in physics, biology, chemistry, and sociology. Similarly, we can use this model to describe cognitively what is happening in a team that is performing an oscillating task. For example, rowing. Each team member observes each other and is drawn to be in the same state at the same time (so that they can row in synchronization).

Despite being a theoretically powerful foundation, this model requires the system to have a set of oscillators that are nearly identical (they all follow the same path). I derive an adaptation of this model that allows for individuals to be in one of a set of discrete states (i.e., performing a given task), and allows each individual to have a different “limit cycle” or natural pattern of transitions among the states they perform. Lastly, the proposed model allows for a generalized interpretation of “proximity” allowing individuals to seek states/tasks that are most helpful to each other instead of requiring them to always seek to perform the same task at the same time.

Figure 9

Illustration of the Kuramoto Model



Note. Illustration indicates only springs connecting other oscillators to a single central figure. The full model would include springs between every pair of oscillators. However, for the sake of clarity, additional springs were excluded. Oscillators rotate around the circle at a natural frequency (indicated by the rotating arrows) but are also influenced by the position of other oscillators (indicated by the springs). This model's spontaneous synchronization is where everyone seeks to be in the same state.

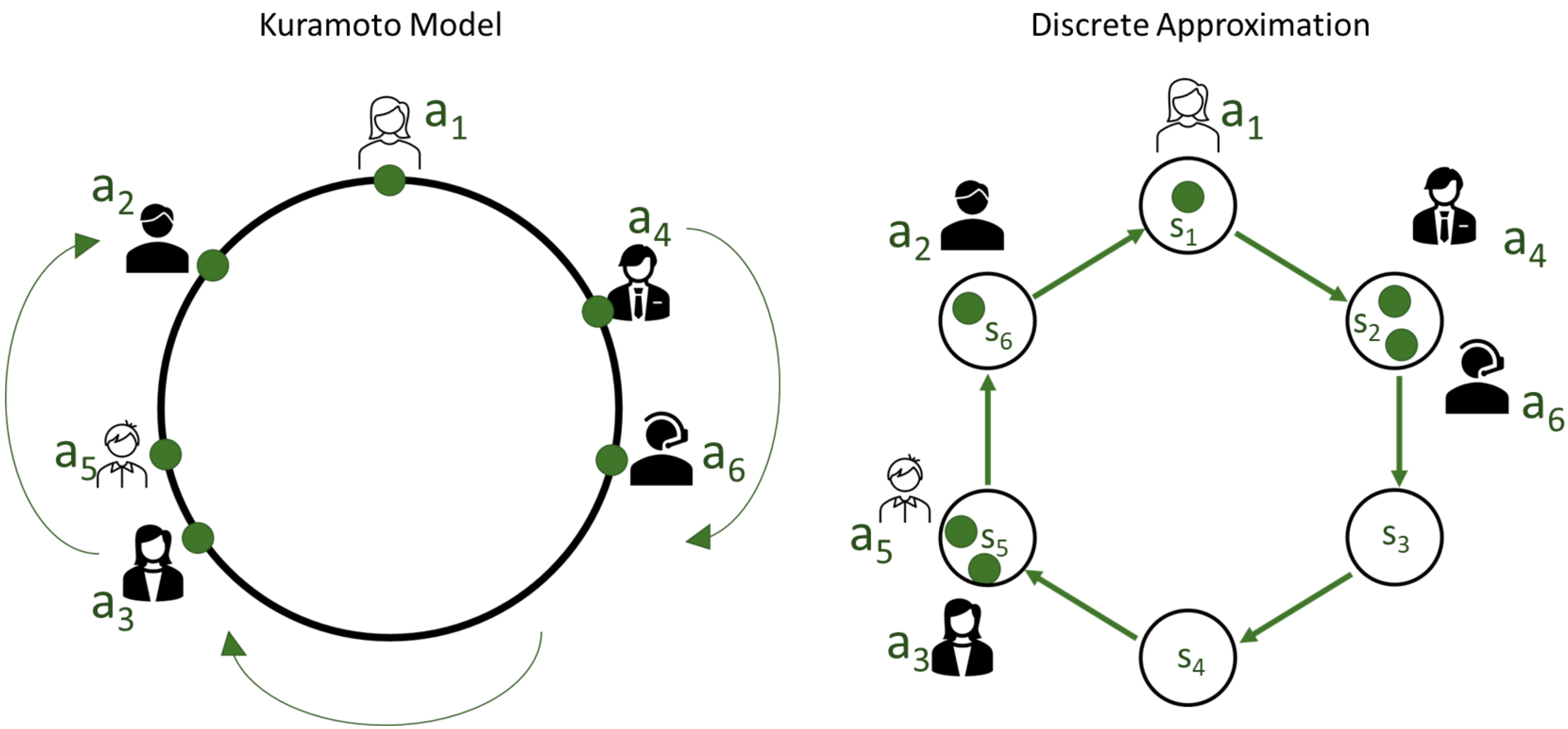
Adaptation of the KM Model for Team-Based Task Work

While the Kuramoto Model (KM) provides an engaging tool to understand emergent synchronization within a team in some instances (e.g., rowing) it has several limitations that make it a poor representation of task work typical of teams. The KM in its original version is helpful for understanding and evaluating deterministic synchronization in nearly identical, loosely coupled oscillators that are near a limit cycle. At first glance, this requires a strong set of assumptions that would appear to typically not apply to teams. Furthermore, the KM is explicitly defined in continuous spaces. While this is ideal for modeling work such as rowing, which can be represented in terms of a single task with individuals at various phases within the given task, it is not immediately clear how this would extend to cases where there are various complex tasks that are not easily represented as oscillatory behaviors. In short, it would be easy to conclude that the applicability of the KM is tied to a very restricted set of team tasks that involve oscillatory behaviors.

I propose simplifying the model by considering discrete space (i.e., a network of states) discrete-time generalizations of the KM. I further generalize the dyadic forces exerted by individual actors on each other such that they do not always drive individuals to want to perform the same task at the same time. To this end, I use a network paradigm, representing each task that a team can perform as a node within a network. Each discrete time step allows individuals to change tasks according to internally identified patterns and preferences. In each time step, each actor's probability of transitioning to a given task will further be adjusted by their teammates. In this way, the network model avoids the determinism inherent in the original KM.

Figure 10

Continuous and Discrete Network Space Kuramoto Models



Note. The continuous space used in the Kuramoto model is approximated by a discrete network of *K* states. This is desirable because it sets us up for representing each discrete state as a distinct task. Individuals transition through the states much as they do in the continuous space Kuramoto model, but each move they make must be a discrete jump from one state to the next instead of being in between. The agents are numbered between 1 and 6 (i.e., a_1, a_2, …, a_6) as are the states (s_1, s_2, …, s_6).

Independent Discrete KM

In our effort to derive a more general representation of the KM, we will start by deriving an independent model, then incorporate interdependence. We start by approximating the continuous space of the KM by dividing the circle (i.e., limit cycle) about which oscillators revolve into *K* distinct states. Oscillators (or agents as I will now refer to them) occupy a given state at a given time. These states can then be presented as a cyclical graph. Distance in this graph is defined by the arc distance between nodes in the cycle graph.

We can model probabilistically what state a given agent will occupy at some time in the future. The oscillatory nature of this system suggests that we consider a probabilistic transition such that each agent is likely to transition some number of states (w) forward around the circle in a single time step. We can further infer that there is some degree of uncertainty (either due to stochastic white noise or due to the error incurred by making the system discrete). So the given agent will most likely transition w steps forward in a single time step, but may transition somewhat more or less than this; see Figure 11. In this section, we will present a formalization of this model and outline the proof that it is equivalent in the limit of time and space to the KM when coupling strength is set to 0.

We begin with the set $A = \{a_1, a_2, \dots, a_n\}$, of n agents (previously referred to as oscillators). Note that for now, we are working with an independent model so each agent moves according to its own internal priorities and is not influenced by others. Let $S = \{s_0, s_2, \dots, s_{m-1}\}$ be a set of m states[2] (or *tasks*) that each agent can be in at a given time t. Note that I define the states m-periodically (i.e., $s_{i+m} = s_i$). Further, define time, $t \in \mathbb{Z}^+$. We define $x_i(t) \in \mathbb{R}^m$ as a

[2] I use the terms *states* and *tasks* interchangeably, based on the context.

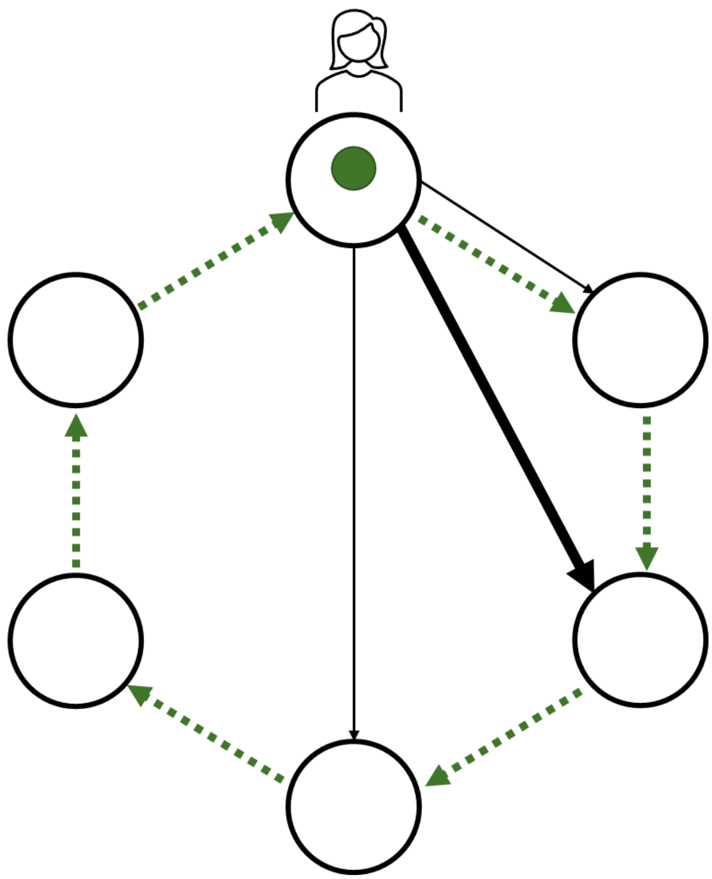
vector such that the k^{th} element of $x_i(t)$ gives the probability that agent a_i will transition to state s_k at time t.

$$x_i(t)[k] \in [0,1] \; s.t. \; |x|_1 = 1, k \in \{1,2,\dots,m\}$$

Now let $\alpha: \mathbb{R} \to \mathbb{R}$ such that for integer values, k, $\alpha(k)$ represents the probability of some agent transitioning from a given state, s_i to another state s_{i+k} independent of the influences of all other agents. Recall also that the states are periodic, so this function will also be *m*-periodic.

Figure 11

Probabilistic Transitions in Network Model



Note. Dashed green lines indicate the natural progression around the set of possible states (tasks). Solid arrows indicate the probability of the agent transitioning to the given positions. The thickness of the arrows indicates the magnitude of the probability. This is an example where, on average, the agent depicted will move forward two states (i.e., w = 2).

$$\alpha: \mathbb{R} \mapsto \mathbb{R}\ s.t.\ |\alpha|_1 = 1,\ \alpha(k+m) = \alpha(k)$$

We can define an $m \times m$ matrix, Ω, where each element $\Omega[i,j] = \alpha(i-j)$ is as follows:

$$\Omega = \begin{bmatrix} \alpha(0) & \alpha(m-1) & \dots & \alpha(1) \\ \alpha(1) & \alpha(0) & \dots & \alpha(2) \\ \vdots & \vdots & & \vdots \\ \alpha(m-1) & \alpha(m-2) & \dots & \alpha(0) \end{bmatrix} \tag{9}$$

Notice that this is a circulant matrix, a fact that will be important soon. We will refer to $\alpha(k)$ as this circulant matrix's *base function*. In the absence of influence from other agents, we can define α such that:

$$x_i(t+1) = \Omega x_i(t) \tag{10}$$

And more generally[3]:

$$x_i(t) = \Omega^h x_i(0) \tag{10a}$$

or

$$x_i(t+h) = \Omega^h x_i(t) \tag{10b}$$

Thus, Ω represents a Markov transition matrix. In the simplest case, we will make assumptions about Ω that allow this to correspond asymptotically with the Kuramoto model. First, take R to be the left permutation matrix operator that shifts rows in the matrix to its right down by one. $R \in \mathbb{R}^{m \times m}$

$$R = \begin{bmatrix} 0 & 0 & \dots & 0 & 1 \\ 1 & 0 & \dots & 0 & 0 \\ 0 & 1 & \ddots & & \vdots \\ \vdots & \ddots & \ddots & & \\ 0 & 0 & \dots & 1 & 0 \end{bmatrix}$$

Set α to be symmetric about some value $w = K\frac{\omega}{2\pi} \in \mathbb{R}$ for $\omega \in \mathbb{R}$:

[3] Note that though this is presented for discrete time, this extends nicely into continuous time representations as well, as long as Ω is diagonalizable. Although Ω^h is not unique for non-integer h, there is a unique solution Ω^h which is also a circulant Markov matrix.

$$\alpha(w+n) = \alpha(w-n)$$

We can now define $\Omega^{\dagger}$ as a symmetric/circulant matrix as follows:

$$\Omega^{\dagger} = \begin{bmatrix} \alpha(w) & \alpha(w+1) & \alpha(w+2) & \dots & \alpha(w+1) \\ \alpha(w+1) & \alpha(w) & \alpha(w+1) & \dots & \alpha(w+2) \\ \alpha(w+2) & \alpha(w+1) & \alpha(w) & \dots & \alpha(w+3) \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \alpha(w+1) & \alpha(w+2) & \alpha(w+3) & \dots & \alpha(w) \end{bmatrix}$$

$$\Omega = R^{w}\Omega^{\dagger} \tag{11}$$

Demonstration of Independent Equivalence. To prove the equivalence of this system with the KM, we need to be able to derive a function $\dot{\theta}_i$ based on the equation for $x_i(t)$. To do this, we can map each state, s_k, to an angle analogous to its position in the circular graph, $\theta(s_k) = \frac{2\pi}{m}k$. We then define a function $\theta\colon \mathbb{R}^m \mapsto [0,2\pi)$ which takes a vector $(x_i(t))$ and maps it to the average angle associated with each of the states that agent a_i could be in at time t weighted by their various probabilities. Define a function $V\colon \mathbb{R}^m \mapsto \mathbb{C}.0$:

$$V(y) = \sum_{k=0}^{m-1} y\,[k] e^{\frac{2\pi i}{m}k}$$

Now define $\theta(y)$:

$$\theta(y) = \frac{1}{i}\operatorname{Log}\frac{V(y)}{|V(y)|}$$

Where *Log* is the complex log operator such that:

$$V(y) = re^{i\theta(y)} \tag{12}$$

For some $r \in \mathbb{R}^{+}$. θ takes the angle implied by the complex number that results from $V(y)$.

Conveniently, we can define v as the left multiplication by a row vector:

$$v^{T} = \left[1, e^{\frac{2\pi i}{m}}, e^{\frac{2\pi i}{m}2}, \dots, e^{\frac{2\pi i}{m}(m-1)}\right]$$

Such that:

$$V(y) = v^T y \tag{13}$$

This is a complex eigenvector of any circulant matrix. The corresponding eigenvalues take the form $re^{\theta i}$ for $\theta \in [0,2\pi)$ and $r \in \mathbb{R}^+$.

To continue we must prove two short results:

Lemma 2: v^T *is an eigenvector of the single row shift permutation matrix,* R*, such that* $v^T R = e^{\frac{2\pi}{m}i} v^T$*, or more generally:*

$$v^T R^{wt} = e^{\frac{2\pi i}{m}wt} v^T \tag{14}$$

Proof:

$$v^T R = \left[e^{\frac{2\pi i}{m}}, e^{\frac{2\pi i}{m}2}, \dots, e^{\frac{2\pi i}{m}(m-1)}, 1\right]$$

$$= e^{\frac{2\pi i}{m}} v^T$$

Next, note that when the exponent of a matrix is defined, the eigenvalues of the power of a matrix are simply the powers of the eigenvalue. R is diagonalizable, therefore in particular:

$$v^T R^{wt} = \left(e^{\frac{2\pi i}{m}}\right)^{wt} v^T = e^{\frac{2\pi i}{m}wt} v^T$$

And we are done.

We now need to prove one more Lemma. But first, we need a definition. Define a P-periodic function f as being **Locally Dense** about some value z if and only if $f(x) \geq f(y) \forall x, y\colon\ |x - z| < |y - z|$. For our purposes, we can relax this condition further to require only that $f(x) \geq f(y) \forall x, y\colon\ |x - z| < P/4, P/4 \leq |y - z| \leq P/2$.

An $m \times m$ matrix, M is defined as being locally dense about the diagonal if and only if the kth column of M is a m-periodic function which is locally dense about k.

Lemma 3: *For any locally dense matrix M that is symmetric and circulant, v^T will be an eigenvector that corresponds to a positive real-valued eigenvalue.*

Proof: Let $f(i) = M[0,i] = M[i,0]$. Further, define f to be periodic so that $f(-i) = M[K-i,0]$. Because M is circulant we know that v^T is an eigenvector of M, and $v^T[0] = 1$, and we only need to look at the first element of $v^T M$ to get the corresponding eigenvalue.

$$\lambda = v^T M[0] = \sum_{j=0}^{m-1} e^{\frac{2\pi i}{m} j} f(j)$$

Set:

$$q = \max_{m/4 \le |y| \le m/2} (f(y))$$

$$\lambda = v^T M[0] = \sum_{j=0}^{m-1} e^{\frac{2\pi i}{m} j} q + \sum_{j=0}^{m-1} e^{\frac{2\pi i}{m} j} (f(j) - q)$$

$$= q \sum_{j=0}^{m-1} e^{\frac{2\pi i}{n} j} + \sum_{j=0}^{m-1} e^{\frac{2\pi i}{m} j} (f(j) - q)$$

Note that $\sum_{j=0}^{m-1} e^{\frac{2\pi i}{m} j} = 0$

$$\ldots = 0 + \sum_{j=0}^{m-1} e^{\frac{2\pi i}{m} j} (f(j) - q)$$

If m is odd, given the periodic nature of $e^{\frac{2\pi i}{m} j}$ we have:

$$\lambda = e^{\frac{2\pi i}{m} 0} (f(0) - q) + \sum_{j=1}^{\lfloor m/2 \rfloor} e^{\frac{2\pi i}{m} j} (f(j) - q) + e^{\frac{2\pi i}{m}(-j)} (f(-j) - q)$$

Given that M is symmetric, $f(-i) = f(i)$

$$\lambda = f(0) - q + \sum_{j=1}^{\lfloor K/2 \rfloor} \left(e^{\frac{2\pi i}{m} j} + e^{\frac{2\pi i}{m}(-j)} \right) (f(j) - q)$$

Further note that $\left(e^{\frac{2\pi i}{m}j} + e^{\frac{2\pi i}{m}(-j)}\right) \in \mathbb{R}\ \forall j$. This is because the imaginary part of this sum is 0. The real part of this sum depends on j. For $|j| < m/4$ trigonometrically we can show the real part is strictly positive. For $m/4 \leq |j| \leq m/2$ it is simple to show trigonometrically that the real part will be non-positive.

$$\lambda = f(0) - q + \sum_{j=1}^{\lfloor m/4 \rfloor} \left(e^{\frac{2\pi i}{m}j} + e^{\frac{2\pi i}{m}(-j)}\right)(f(j) - q) + \sum_{j=\lfloor m/4 \rfloor + 1}^{\lfloor m/2 \rfloor} \left(e^{\frac{2\pi i}{m}j} + e^{\frac{2\pi i}{m}(-j)}\right)(f(j) - q)$$

We know that $f(0) > q$ so the first part is positive. For $|j| < m/4$, we know $\left(e^{\frac{2\pi i}{m}j} + e^{\frac{2\pi i}{m}(-j)}\right) > 0$ and $(f(j) - q) > 0$ so the second part is positive. Lastly, for $m/4 \leq |j| \leq m/2$ we know $\left(e^{\frac{2\pi i}{m}j} + e^{\frac{2\pi i}{m}(-j)}\right) \leq 0$ and $(f(j) - q) \leq 0$ so the third part is positive. Collectively, this proves that $\lambda \in \mathbb{R}$ and $\lambda > 0$.

If m is even, the same logic will hold with the addition of one extra term (i.e., representing the point exactly halfway around the circle). We find the following:

$$\lambda = f(0) - q + e^{\pi i}(f(m/2) - q) + \sum_{j=1}^{\lfloor m/4 \rfloor} \left(e^{\frac{2\pi i}{m}j} + e^{\frac{2\pi i}{m}(-j)}\right)(f(j) - q)$$

$$+ \sum_{j=\lfloor m/4 \rfloor + 1}^{\lfloor (m-1)/2 \rfloor} \left(e^{\frac{2\pi i}{m}j} + e^{\frac{2\pi i}{m}(-j)}\right)(f(j) - q)$$

$$= f(0) - f\left(\frac{m}{2}\right) + \sum_{j=1}^{\left\lfloor \frac{m}{4} \right\rfloor} \left(e^{\frac{2\pi i}{m}j} + e^{\frac{2\pi i}{m}(-j)}\right)(f(j) - q) + \sum_{j=\lfloor m/4 \rfloor + 1}^{\lfloor (m-1)/2 \rfloor} \left(e^{\frac{2\pi i}{m}j} + e^{-\frac{2\pi i}{m}j}\right)(f(j) - q)$$

The summations must both have non-negative values for the same reasons as in the odd case. Further, $f(0) - f(K/2) > 0$ because f is locally dense about 0. With that, we have proven Lemma 3.

Theorem 1: *The discrete network model presented in Equation 10a is equivalent to the KM when the coupling strength is 0.*

Proof:

Using Lemmas 2 and 3 we have the following result:

$$V(x_i(t)) = v^T \Omega^t x_i(0) = v^T R^{wt} \Omega^{\dagger t} x_i(0)$$

Set $\omega = \frac{2\pi w}{m}$:

$$= r_1 e^{\omega t i} v^T x_i(0)$$

Define $\theta_0 = \theta(x_i(0))$.

$$= r_2 e^{(\theta_0 + \omega t) i}$$

For some $r_1, r_2 \in \mathbb{R}^+$.

$$\theta(x_i(t)) = \theta_0 + \omega t \tag{15}$$

Taking the derivative of this yields the expected independent result from the KM when the coupling strength is set to 0:

$$\frac{d\theta_i}{dt} = \omega$$

For this to work, the functions $x_i(t)$ and $\theta(y)$ must both be continuous and differentiable in t. That means they must be defined for $t \in \mathbb{R}$, not just discrete t values. However, this is true. Specifically, Ω is diagonalizable because it is a real circulant matrix and therefore Ω^t is well defined for $t \in \mathbb{R}$. Similarly, $\theta(y)$ is differentiable for $|V(y)| \neq 0$. Thus we have demonstrated that in the independent case (coupling strength set to 0), the KM model is equivalent to the network model presented here.

As defined here, Ω is necessarily circulant, implying that actors transition from task to task circularly. Later, we can relax this restriction and generalize so that Equation 10 represents the probabilistic state that each agent will be in at some given point in the future based on their own unique transition matrix Ω. This is well defined for continuous-time as long as Ω is diagonalizable, and is always well defined for discrete-time, $t \in \mathbb{Z}^{+}$.

$$x_i(t) = \Omega^t x_i(0)$$

Formally Modeling Interdependence

Having established a foundation for the CSN model the next goal is to extend this discrete KM model to account for interdependence on the state of all other agents. Define *X* as an *m*-by-*n* matrix where the i^{th} column represents the probabilistic task/state transition of agent *i*.

We can use an expectancy theory/utility-based motivational paradigm to derive this function given a few assumptions. Note that the KM essentially describes a system of oscillators that are motivated to be proximal to each other. The interdependence in their motion provides rewards and punishments for moving to states (i.e., performing tasks) that are proximal to each other. From this perspective, I define a utility associated with choosing to move to each state.

Building on the three components of expectancy theory, the closer a potential state is to a teammate the higher the valence (i.e. value) and the more an agent will want to choose to move to the given state. Additionally, the more that agents believe making a given move will get them closer to the desired state (proximity to others) the more they will be motivated to make a given move. This is *instrumentality*. On the other hand, the further the state is from the state they were going to go to on their own the lower the *expectancy*. This suggests it is more difficult, or less rewarding to make larger deviations from their course as opposed to small deviations. More generally this reflects the difficulty of switching to the given state.

Loosely following the expectancy value's proposed multiplicative relationships I define two curves. One (E-Curve) reflects the *expectancy* or difficulty of making a given move. The other (IV-Curve) represents a combination of instrumentality and valence. Similarly to the multiplicative proposition of expectancy theory, we can take the point-wise product of these curves, then normalize them to establish the total utility of a given move[4]. I refer to the normalized point-wise product of these two curves as the utility curve (U-curve).

Before directly applying this work to the KM generally, we consider a non-oscillating single-dimensional system where there is exactly one agent that is driven to move closer to some target state (representing a teammate's position they are responsive to). This agent also has a natural velocity, w. After establishing how things work in this non-oscillating scenario, we will expand this to reflect the oscillating system with multiple agents influenced by each other as described by the KM.

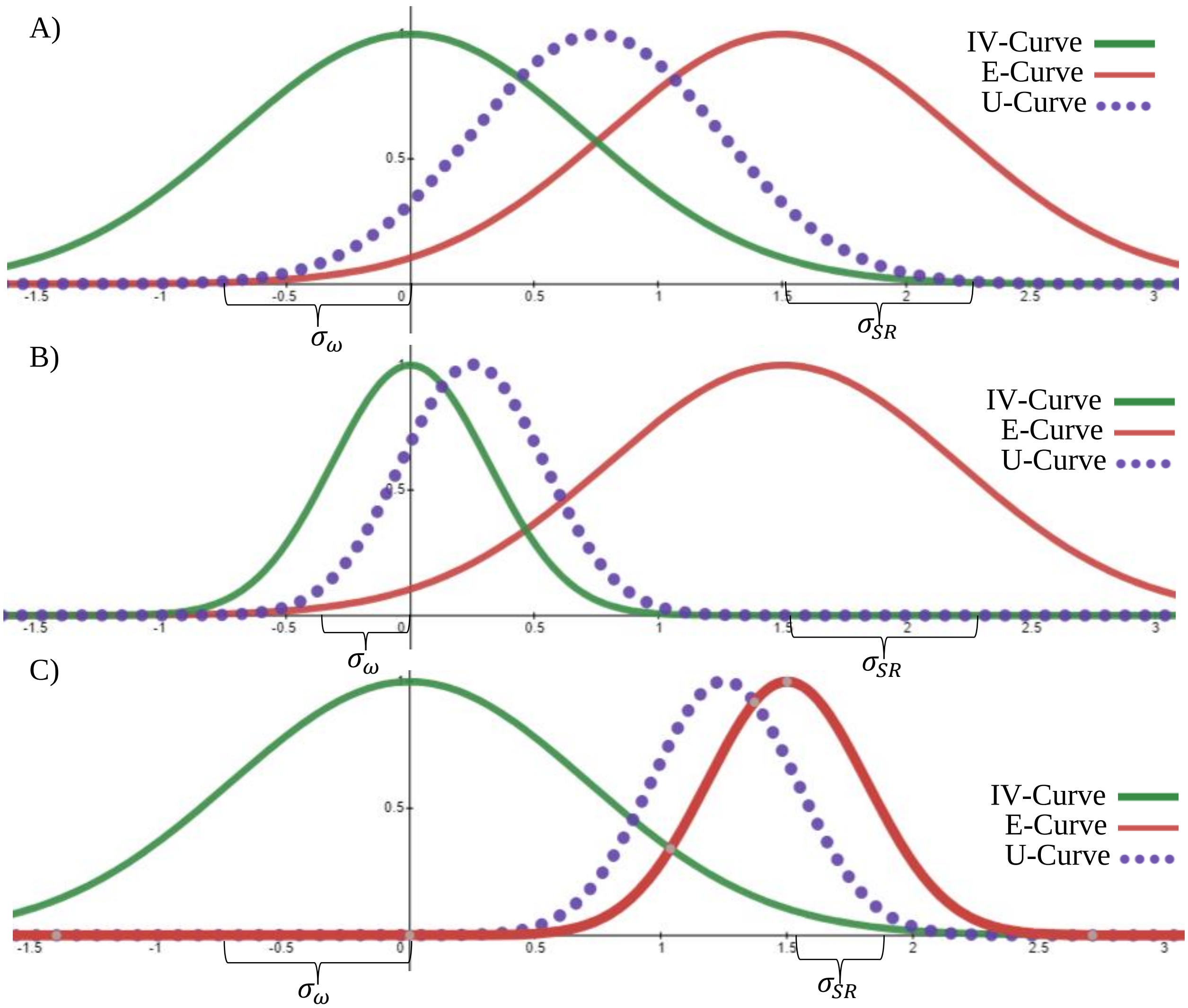
If we fix the IV-curve's shape and adjust the variability in the E-curve we see that the less the variability in the E-curve, the closer the agent's motion will reflect its natural velocity. This is conceptually analogous to the notion of mass as described by Newtonian physics because the less variability in the expectancy curve (lower mass), the harder it is for external influences to change the agents' course of action. Noting this, for now, we will assume that the variance of the expectancy curve is fixed as σ_{ω}^{2}.

The utility curve encodes how much the agent is drawn to the target position. If we fix the E-curve and adjust the variance in the IV-curve, the impact on total utility is clear. The more closely the density of the Gaussian-valence curve is clustered around the target state's position, the stronger the pull of the target on the agent (See Figure 12). Thus the variance of the IV curve reflects the strength of attraction. This is closely related to the notion of *coupling strength* found in the KM. Instead of *coupling strength,* I will refer to this as *Social Responsiveness* (SR)

[4] There are known issues with the multiplicative assumption of expectancy theory. However, by multiplying distributions instead of scalers this model avoids many of these known issues.

Figure 12

Illustration of Normalized Product of Gaussian IV- and E-Curves



Note. The green line indicates the expectancy curve centered around 0 indicating that the further from one's current state the more difficult a given transition is. The red line indicates the valence/instrumentality curve centered around 1.5. The motivational force or utility of any transition is given by the normalized point-wise product of these two curves (purple dotted line). When the variances are even (top) the product curve is centered halfway between them. But when there is less variance in the E-curve (middle) or IV-curve (bottom) the product curve is biased toward the curve with less variance. The standard deviations of these curves are σ_ω and σ_{SR}.

noting its close relationship to the concept of *in situ* coordination. The greater the SR strength the more the agent is exposed to, cares about, and responds to the position of the target. While this accounts for the valence of performing tasks that are proximal to a teammate (i.e., how much does the agent care about the target) it also incorporates notions of instrumentality (i.e., how much does the agent believe the given action will bring them closer to the desired reward) and even salience (i.e., how aware is the agent of the target in the first place). This variance will be represented as σ_{SR}.

The point-wise product of two Gaussian curves is another Gaussian curve. Specifically, if we define the IV-curve by a function $g_{IV}(x) = PDF[N(j, \sigma_{SR}^2)]$, and define the E-curve by a function $g_{\Omega}(x) = PDF[N(w, \sigma_{\omega}^2)]$, the normalized point-wise product (i.e., the U-curve) is defined as follows:

$$g_u(x) = PDF\left[N\left(\frac{\sigma_{SR}^2 w + \sigma_{\omega}^2 j}{\sigma_{SR}^2 + \sigma_{\omega}^2}, \frac{1}{\frac{1}{\sigma_{SR}^2} + \frac{1}{\sigma_{\omega}^2}}\right)\right]$$

In this simple, single-dimensional example the expected change in the agent's location in one time step is then given by the mean of the utility curve.

$$\frac{\sigma_{SR}^2 w + \sigma_{\omega}^2 j}{\sigma_{SR}^2 + \sigma_{\omega}^2}$$

To derive a discrete-space, discrete-time representation of the KM we will incorporate these concepts into the equation of the future state of a given agent. Using this, we derive an equation for σ_{SR}^2 given a fixed value of σ_{ω}^2 such that the resulting change in an agent's position will be equal to the change predicted by the KM.

Single-Agent Oscillating System. The concept described here becomes more complex once you account for the fact that the states described by the KM are periodic. Specifically, the point-wise product of two periodic functions is not Gaussian anymore. However, if the variances of these nearly Gaussian IV- and E-curves are small in relation to the period length the resulting U-curve will be essentially Gaussian. We will discuss this in more detail later, but for now, it is sufficient to assume the following:

$$\sigma_{SR}^2, \sigma_{\omega}^2 \ll m$$

Two Distance Measures. It should be emphasized that distance in the KM is defined in two ways. The first type of distance is represented as the *transition-distance*. The transition distance represents how far an actor actually travels (or how difficult it is) when transition from their current state to another. In the present KM based example, this is defined as the arc-distance between states, indicating that actors move along the circumference of the circle. In this way the distance between any two states s_i and s_j is proportional to $i - j$. Specifically, we use the θ function defined previously to define the arc-distance between two states s_i, and s_j.

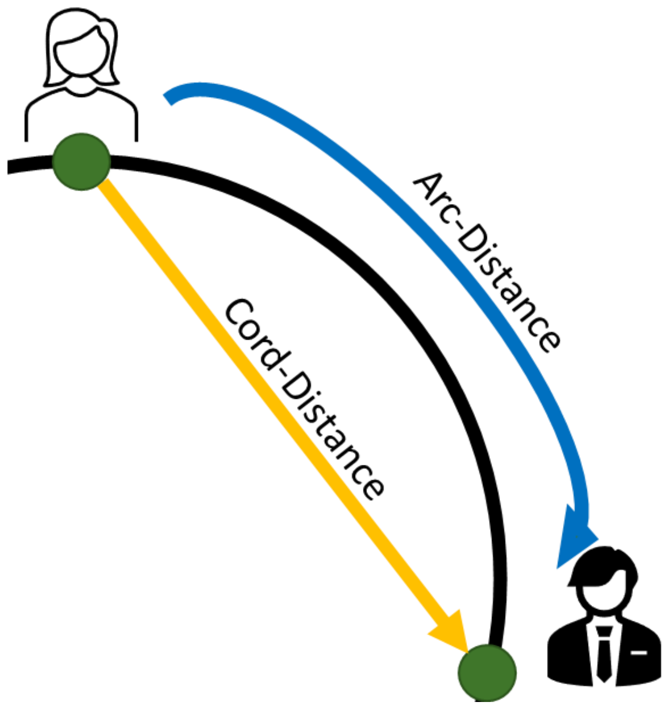
$$d_{arc}(s_i, s_j) = \theta(s_i) - \theta(s_j)$$

Additionally, there is an *influence-distance*. When actors are influenced by each other, the further they are the less they influence each other. This is related to the concept of instrumentation. The idea is that the further a target state is from one's current state the less the actor believes that their effort will result in desired outcomes. This form of distance will depend on various factors but in the present KM based example it is measured by cord-distance cutting through the circle that the agents are set on. This is the shortest line connecting points across the center circle that the states are projected onto. To do this I project the states s_i, and s_j onto the normed space that defines the circle. This is defined more rigorously later using the spectral decomposition of the circular graph. For now, it is sufficient to define a function, $v^{\star}: S \mapsto \mathbb{R}^2$.

$$d_{cord}(s_i, s_j) = |v^{\star}(s_i) - v^{\star}(s_j)|_2$$

Figure 13

Illustration of Distance of Transition vs. Distance of Influence



Note. Arc-distance represents the actual distance an actor must transition through to get to the target state. Cord-distance represents the distance across which team influences will act. In the KM, the actors influence each other through direct lines, but actors must move around the circumference of the circle. In a more general sense, the transition-distance is defined by the Ω matrix, while the distance of influence is used to define the curves found in the columns of the V-matrix. The ratio of these is theoretically relevant to instrumentality.

Time Step Size and Ω. We now use the expectancy-curve idea to more clearly define Ω. Ω is an *m*-by-*m* matrix with columns corresponding to the previous state and rows corresponding to the new state. Each entry in Ω conceptually gives the likelihood of transitioning from the state corresponding to the column to the state corresponding to the given entries row. Define Ω as a circulant matrix where each column represents the expectancy curve if the agent were at the state corresponding to that column. Here we are defining the circulant base function α (see Equation 9) as $PDF[N(w, \sigma_{\omega}^2)]$.

To derive a discrete-time model asymptotically equivalent to the continuous time KM, we must consider time. In particular, we must define Ω as a function of the time step size so that we can evaluate the system as the time step dissipates to 0. To do this we must prove one result first.

Lemma 4. *Take a circulant matrix, M, with a Gaussian base function centered at μ (j is the column) and variance, σ^2. M^h will be circulant with Gaussian columns centered at hμ and variance hσ^2 for $h \in \mathbb{Q}$.*

Proof:

To prove this we need to leverage two known facts:

1) Multiplication on the left by a circulant matrix is the discrete equivalent of taking the convolution of the base function and defining the circulant matrix with a vector or the columns of a matrix.
2) The convolution of two normal (or Gaussian curves) is Gaussian such that:

$$N(\mu_1, \sigma_1^2) * N(\mu_2, \sigma_2^2) = N(\mu_1 + \mu_2, \sigma_1^2 + \sigma_2^2)$$

Leveraging these two facts, we know if *h* is an integer that M^h is equivalent to *h* matrix-multiplications of *M* with itself. Given fact 1), each of these matrix multiplications produces a matrix with columns representing convolutions. In particular, the columns of M^h will be *h* convolutions of a Gaussian with itself. If the original base function of *M* is centered at μ with variance σ^2 the base function for the circulant matrix M^h will be centered at $h\mu$ with variance $h\sigma^2$.

Thus the result holds whenever *h* is an integer. Consider the case where *h* is one over an integer: $h = \frac{1}{q}, q \in \mathbb{Z}$ Let Q be the circulant matrix with Gaussian base function centered at $h\mu$

and with variance $h\sigma^2$. Because $q \in Z$ we know that Q^q will be circulant with Gaussian based function centered at $qh\mu = \mu$ with a variance of $qh\sigma^2 = \sigma^2$. Thus $Q^q = M$.

Because circulant matrices are diagonalizable M^h is well-defined (though not unique). In particular, there exists a solution:

$$M^h = (Q^q)^h = Q$$

We can scale the time step by a factor $h < 1$ simply by taking Ω to the power h. Conveniently by defining Ω as a circulant matrix with Gaussian columns, we ensure that we can equivalently take this power by multiplying the mean and variance of the *Ω's* defining a Gaussian function by *h*. We can use these results to quickly extend the result to all $h \in \mathbb{Q}$.

Notably, this work utilizes results that are dependent on the functions being continuous. For example, multiplication by a circulant matrix is equivalent to a discrete convolution, but fact two above is only necessarily true for convolutions of continuous functions. This will be true in the limit $m \to \infty$, which is sufficient for our needs.

V and *In Situ* Coordination. To account for interdependence the model takes the Hadamard (elementwise) product of Ω^h and a Valence/Instrumentality matrix *V*. Then normalize (done by multiplying by D). As with Ω^h the columns of *V* are assumed to be Gaussian functions. For *V*, the functions are each centered at the target location (we will use *j* to refer to the target location). As a reminder, for the present time, we assume there is one agent that is influenced by a single fixed target – later we will extend this to account for the impact of agents responding to multiple other agents.

$$x(t + h) = (V \odot \Omega^h)Dx(t) \tag{17}$$

Unlike Ω^h, *V* will not be circulant. Additionally, each column will incorporate not only the valence of proximity to the target state – which will be the same regardless of where the agent is coming from – but will also incorporate notions of instrumentality that differ based on the current state of the agent.

As noted previously, the point-wise product of two Gaussian curves is Gaussian. By taking the Hadamard product of two matrices with columns that are Gaussian we are approximating this result. The resulting matrix will therefore have columns that approximate a Gaussian U-curve:

$$g_u(x) = PDF\left[N\left(\frac{\sigma_{SR}^2 w + \sigma_\omega^2 j}{\sigma_{SR}^2 + \sigma_\omega^2}, \frac{1}{\frac{1}{\sigma_{SR}^2} + \frac{1}{\sigma_\omega^2}}\right)\right]$$

Before continuing we must prove another Lemma.

Lemma 5: *Define M as a circulant matrix with a symmetric base function f that is locally dense about μ. Let $x \in R^m$, $\theta(Mx) = \mu + \theta(x)$*

Proof:

Taking the rotational permutation of *M* we get:

$$M^\star = R^{-\mu} M$$

Where $M^\star$ is by design locally dense about the diagonal. By Lemma 2

$$v^t M^\star x = r v^t x, \text{ for } r \in \mathbb{R}^+$$

$$\Rightarrow \theta(M^\star x) = \theta(x)$$

At the same time

$$v^t M^\star x = v^t R^{-\mu} M x$$

$$= e^{\frac{2\pi i}{m}(-\mu)} v^t M x = e^{\frac{2\pi i}{m}(-\mu)} r e^{i\theta(M)} v^t x$$

$$\Rightarrow \theta(Mx) = \frac{2\pi\mu}{m} + \theta(x)$$

Deriving $\boldsymbol{\sigma_{SR}^2}$. Deriving the variance σ_{SR}^2 by setting a discrete approximation of the velocity $\frac{\theta(x(t+h))-\theta(x(t))}{h}$ equal to the KM's equation for the instantaneous angular velocity of agent *I* as follows:

$$\Delta_h\theta(x(t)\,) = \frac{\theta(x_i(t+h))-\theta(x_i(t))}{h} = \omega_i + K\sin(\theta_i - \theta_j)\,,$$

and assuming that the agent's position is deterministic so that the $\mathrm{x_i}(t)$ has one element that is 1, and all others are 0. Let the state of agent *i* at time *t* be *s*. We get that $x_i(t+h) = (V \odot \Omega^h)Dx_i(t)$ will be a vector equal to the element-wise product of the *s^th^* columns of V and Ω^h. This vector is symmetric about some central value.

$$\mu = \frac{\sigma_{SR}^2\theta_s + h\sigma_\omega^2\theta_j}{\sigma_{SR}^2 + h\sigma_\omega^2}$$

$$\Rightarrow \theta\big(x(t+h)\big) = \mu$$

Without loss of generality, we can set $\theta_i = \theta\big(x_i(t)\big) = 0$. (In other words $s = 0$). Notably, this implies that *j* is defined such that $\theta_j = \theta_j - \theta_i$. As such I will write this θ_d for difference. We can further simplify removing the natural frequency by defining $\theta^*(y(t)) = \theta(y(t)) - \omega_i t$. (remember $\omega_i = \frac{2\pi}{m}w_i$.)

This gives us:

$$\Delta_h\theta(x(t)\,) = \frac{\theta\big(x_i(t+h)\big) - \theta\big(x_i(t)\big)}{h} = \frac{\theta^\star\big(x_i(t+h)\big)}{h} + \omega_i$$

$$= \frac{\sigma_\omega^2\theta_d}{\sigma_{SR}^2 + h\sigma_\omega^2} + \omega_i$$

Setting this equal to the KM we get:

$$\Delta_h\theta(x(t)\,) = \omega_i + K\sin(\theta_d)$$

$$\Rightarrow \frac{\sigma_\omega^2 \theta_d}{\sigma_{SR}^2 + h\sigma_\omega^2} = K\sin(\theta_d)$$

Solving for σ_{SR}^2

$$K(\sigma_{SR}^2 + h\sigma_\omega^2)\sin(\theta_d) = \sigma_\omega^2 \theta_d$$

$$K\sigma_{SR}^2 \sin(\theta_d) = \theta_d \sigma_\omega^2 - Kh\sigma_\omega^2 \sin(\theta_d)$$

$$\sigma_{SR}^2 = \sigma_\omega^2 \left[\frac{\theta_d}{K\sin(\theta_d)} - h\right]$$

Importantly this variance is dependent on the current relative difference in position (18) between the agent (θ_i) and the target state (θ_j). When we generate a matrix based on Gaussian curves centered at *j*, each column represents a different current location for agent *i*. As such this variance will differ for each column. On the other hand, regardless of where the agent is currently, the position of the target remains stable.

To conclude, we will reorganize this equation to aid in developing an intuition for its theoretical meaning. First, define r_d as the ratio of arc-distance ($d_{arc} = \theta_d$) and cord-distance ($d_{cord} = \left|v^\star(s_i) - v^\star(s_j)\right|_2$)

$$r_d = \frac{d_{arc}}{d_{cord}}$$

Next note the following (for illustration see Figure 14): Where ρ is the angle between the tangent at s_i and the cord between s_i and s_j.

$$\frac{d_{cord}}{\sin\theta_d} = \frac{1}{\cos\rho}$$

Finally, this gives us:

$$\sigma_{SR}^2 = \sigma_\omega^2 \left[\frac{r_d}{K\cos\rho} - h\right] \tag{19}$$

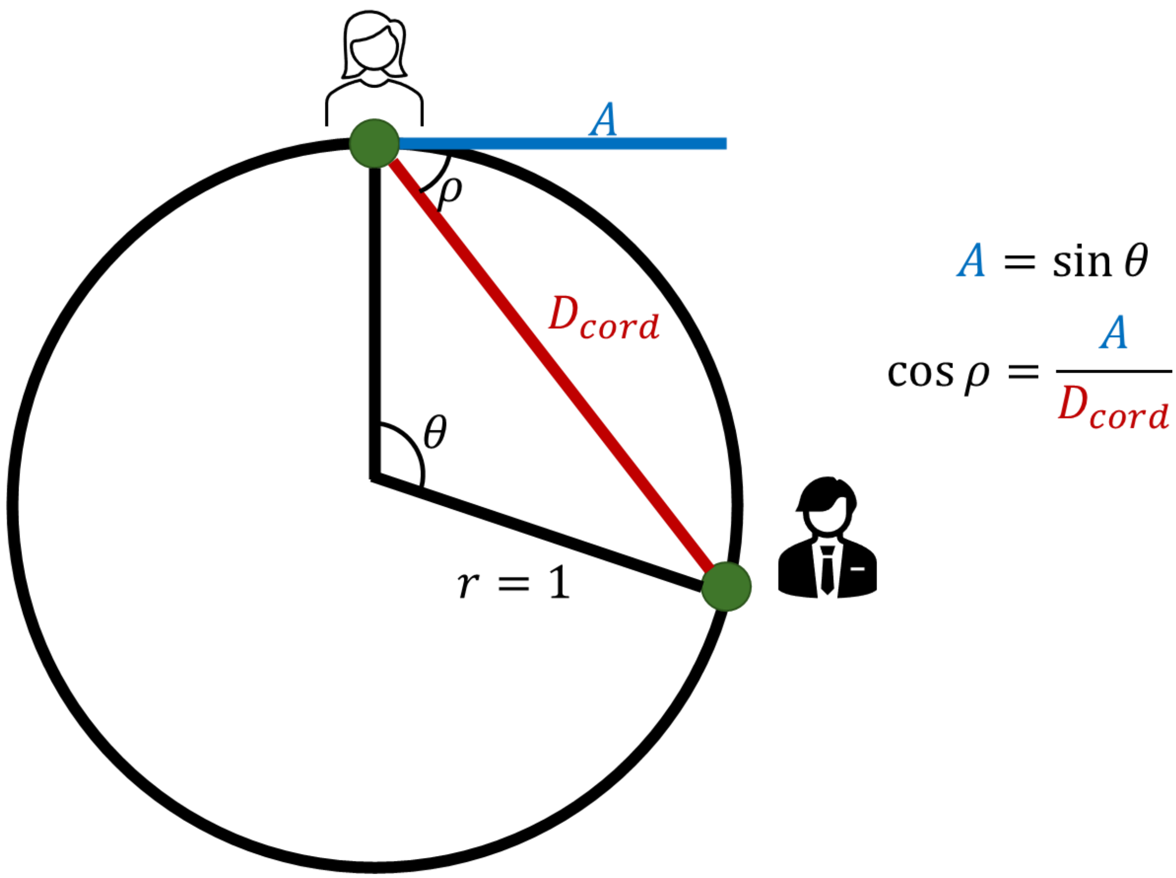
With this, we are prepared to finalize the discrete time and discrete space representation of the KM. Before doing so we will pause and discuss the intuition behind this equation.

One last note, the variability in the curve that $x_i(t+h)$ defines will be equal to

$$\frac{1}{\frac{1}{\sigma_{SR}^2}+\frac{1}{\sigma_{\omega}^2}}$$

Figure 14

Illustration of Similarity Ratio



Note. The cosine of ρ represents the similarity of the direction of motion (i.e., A) and the direction of influence (i.e., D_{cord}).

Theoretical Interpretation of $\boldsymbol{\sigma_{SR}^2}$ Equation. The variance of any column of the *V* matrix represents how strongly the target state influences the agents' movements. If there is no variance (i.e., the column is a delta function) then the agent will always move to the exact position of the target. If the variance is infinite (i.e., the column is uniform) then the target has no impact on the movement of the agent.

There are five components of Equation 19 above. Each component is described and the intuition behind their impact discussed. First σ_{SR}^2 is directly proportional to σ_{ω}^2. This has relatively little theoretical importance and can mainly be thought of as a scaling factor. Because of this relationship, however, we can increase the total precision of $x_i(t+h)$, to arbitrarily high by simply decreasing the variance of the base function for Ω. The second feature of note is the solo *h*. This represents a correction factor for discrete-time effects. As the timestep decreases in size to zero, this factor has a diminished overall effect. Again, there is little theoretical importance here, as this reflects the impact of using a discrete representation.

The remaining three features are all theoretically meaningful. First, K is closely related to the notions of *social responsiveness* and coupling strength. From an expectancy theory perspective, *K* is essentially a measure of the utility associated with proximity to the target state. The larger *K* is the smaller the variance of σ_{SR}^2 and the stronger the draw to the target state will be. Next both the r_d and the $\cos\rho$ terms are related to the concept of instrumentality. Specifically r_d is the ratio between the straight line distance from the agent to the target, and the actual distance that the agent would travel to get to the target. The larger this ratio is the weaker the connection between the agent’s efforts and the desired state of being proximal to the target. In other words, greater values of r_d represent weak instrumentality, and as such large r_d values will diminish the influence the target has on the agent. The $\cos\rho$ term is likewise related to the concept of instrumentality. Specifically, this term gives the inverse of the cosine similarity between the direction of motion an agent must travel and the direction (across the circle) that they are being pulled. If these directions are orthogonal this suggests that no possible movement by the agent will immediately bring it closer to the target. As such, the agent would experience critically low levels of instrumentality. On the other hand, when these two directions are nearly parallel, this term will approach the value 1, indicating that the instrumentality of the given move is high.

Thus, the equation for σ_{SR}^2 (Equation 19) provides theoretical insight into the impact of valence and instrumentality associated with moving toward a desired state.

Multiple Agents. The final step in describing this system is to incorporate multiple agents. Specifically, thus far the system has been identified with only one agent and a fixed target state. We will now extend this to apply to systems of n agents that all impact each other.

The extension is straightforward. Specifically, we can define V_{ij} as the independence factor accounting for the impact of agent *j* on *i*. Note that $V_{ii} = I$. To account for multiple sources of influence we simply calculate new independence factors for each one and take their product.

$$x_i(t+h) = [V_{i1} \odot V_{i2} \odot \ldots \odot V_{im} \odot \Omega^h] D x_i(t) \tag{20}$$

Without loss of generality, we assume that $\theta_i = 0$. With this, we can calculate $\theta\big(x_i(t+h)\big)$ based on the first column of $[V_{i1} \odot V_{i2} \odot \ldots \odot V_{im} \odot \Omega^h]$. Instead of calculating σ_{SR}^2 separately for each alter agent's location, we hold σ_{SR}^2 constant for each column across all *V* matrices. This is done by calculating θ_d based on the difference between θ_i and the average θ for all agents. Following the KM's design, we divide *K* by *N*. Based on this we get the following:

$$\theta^{\star}\big(x_i(t+h)\big) = \frac{\sigma_{\omega}^2 \sum_j \frac{\theta_j}{n}}{\sigma_{SR}^2 + \sigma_{\omega}^2} + \omega_i$$

From here it is straightforward to show:

$$\Rightarrow \Delta_h\big(x_i(t+h\,)\big) = \omega_i + \frac{K}{n}\sum_j \sin\theta_j - \theta_i$$

This is equivalent to the KM (Kuramoto, 1984).

Equivalence to KM. By construction, the CSN described here is equivalent to the complete KM in the limit on the number of discrete states (i.e., m) and the limit on the size of the discrete-time interval (i.e., $\lim h \rightarrow \infty$).

There are various points where the proof thus far is not complete. Specifically, math repeatedly relies upon discrete approximations of continuous functions. Further work will need to demonstrate in each case the appropriateness of these approximations and whether the limits applied at the end sufficiently demonstrate equivalence to the KM. Furthermore, the relationships described here were originally applied to non-oscillating systems. Because the system is periodic, these relationships may have other issues. I posit that in each case appropriately allowing the number of states to increase, the time to decrease, and the base σ_{ω}^2 variance to decrease will be sufficient but leave the rigorous proof as an exercise for future work.

Generalization of the CSN Model

$$x_i(t+h) = \left[P_i \odot V_i \odot \Omega^{\mathrm{h}}\right] D x_i(t) \tag{21}$$

As described thus far, the formal CSN model (Equation 21) is not particularly useful for understanding teams. Both Ω and V are under strict assumptions that make the model act in an oscillatory manner equivalent in the limit to the KM. However, these strong requirements are not needed. Specifically, the model as presented here applies to numerous scenarios that have significantly relaxed assumptions. In this section, I will briefly describe the components of the CSN model theoretically and discuss multiple forms that these could take. I will also extend the CSN to account for *a priori* coordination efforts using the matrix P.

Table 2

Mathematical Notation Used in the Formalized CSN Model

Value	Symbol	Shape	Description
Individual State	x	m	A vector encoding the probability of actor *i* being in a given state at time *t*.
Expectancy Matrix	Ω	$m \times m$	A matrix encoding how likely/difficult the transition from any one state to any other state for the given actor. This defines the notion of distance.
Valence/ Instrumentality Matrix	V	$m \times m$	A matrix encoding how valuable transition to a given state will be (valence) as well as how much a given transition will bring the actor closer to the desired state (instrumentality).
Plan Matrix	P	$m \times m$	A matrix encoding the *a priori* model for what individuals believe they should perform at a given time. This is affected by precision in both temporality, and precision in ability to distinguish states (tasks).
Normalization Factor	D	$m \times m$ (diagonal)	A diagonal matrix with values used to standardize Equation 21 such that the result is a proper Markov matrix.

Note. ND stands for nondimensionalized symbols. The Motivator Strength m, Ready State Loss l_R, and Independence Constant β_U are all treated as model constants with the characteristic values and removed from the non-dimensional equations.

Expectancy (Ω)

First, we will consider Ω. This is the natural transition matrix encoding what states/tasks a person is likely/able to transition to, given what they are currently doing. While it has thus far taken a circulant form (in effect assuming regular oscillation) it does not need to. Any K-dimensional Markov transition matrix could be appropriate here. The point is that Ω encodes the probabilistic transitions that a given actor will follow in the absence of external influence.

To illustrate just one alternative form, let us consider an example where one person always shifts to a specific task (resetting) whenever they complete other tasks. At any given time point they have a fifty-percent chance of resting or continuing with their task. When they are done, they have a fifty-percent chance of continuing resting and the remaining 50-percent chance is split between starting any of the remaining tasks. In this example, Ω would look something like the following:

$$\Omega = \begin{bmatrix} .5 & .5 & .5 & .5 & \dots & .5 \\ \frac{.5}{K-1} & .5 & 0 & 0 & \dots & 0 \\ \frac{.5}{K-1} & 0 & .5 & 0 & \dots & 0 \\ \frac{.5}{K-1} & 0 & 0 & .5 & \ddots & \vdots \\ \vdots & \vdots & \vdots & \ddots & \ddots & \\ \frac{.5}{K-1} & 0 & 0 & \dots & & 0 \end{bmatrix}$$

The first row of all $.5$'s represents the fact that from any previous state, agents have a 50-percent chance of deciding to transition to the first state - *resting*. The remaining rows all have a .5 on the diagonal, representing the fact that they have a 50-percent chance of remaining at a given task. The first column represents the fact that from the resting state, there is a 50-percent chance that the agent will keep resetting, and the remaining 50-percent probability is split among all the remaining states.

This is just one example of the types of shapes that Ω could take. The columns of Ω must sum to 1, and it must be an $m \times m$ matrix. Additionally, it is assumed that Ω has positive values. These are the restrictions of a Markov matrix. But otherwise, it can have any form within these restrictions that is desired.

In many teams, the tasks are divided such that each team member is responsible for a specific set of tasks. Otherwise, individuals may simply have strong preferences for some tasks.

In this case, there will be specific rows in Ω_i that have a much higher total than other rows. Tasks frequently performed by agent a_i will have a large corresponding row sum in Ω_i while tasks infrequently performed by agent a_i likely have a much smaller corresponding row sum.

It should be noted that conceptually Ω_i represents the tasks that the given agent, a_i, is capable of performing/believes they are capable of performing. If someone frequently performs tasks that they are not assigned, this should be reflected in a larger corresponding row sum in Ω_i although they are not formally assigned to that task.

Social Responsiveness (κ)

Next, I note that κ may have various forms. As defined here it is a single value that is held constant across members of the team. However, it may be better represented as an individual characteristic (i.e., some people are more socially responsive than others) or a dyadic characteristic (i.e., some people respond more to specific others). In many cases, I suggest that a network-based representation of κ with dyadic values is merited. However, it is reasonable to assume that the disparities in κ values will be limited in some cases. In such cases, using a single κ value represents a reasonable approximation of how the team will function.

Instrumentality

As defined above, the instrumentality is found within the equation for σ_{SR}^2:

$$\frac{r_d}{\cos\rho}$$

This is effective for representing the instrumentality of transitioning to a state s_k concerning the goal of being proximal to a_j. However, the way this works is specifically tied to the notion that tasks are distributed in a circle and the difficulty of changing from one task to another is related to the arc distance between the two tasks. This idea of instrumentality can be generalized. Specifically, in the circular case this represents the ratio of distance traveled compared to straight line distance, as well as a measure of the similarity between the initial trajectory an agent will follow and the direct trajectory of influence. I define an instrumentality coefficient ξ that generalizes these ideas.

The assumption that for any agent to move to another state requires a change of some distance is in effect; however, there will be a lesser change in the distance upon which the force acts. The product of this ratio and the inverse of the cosine similarity between the trajectory of influence and the trajectory of motion will be defined as ξ, the instrumentality parameter. In cases where motion is not restricted to some path, this value will be 1.

Interdependence Networks and Redefining Distance

Thus far, interdependence as used here could be defined by a circular interdependence graph, where individuals are driven to move to network positions most proximal to others. This simple set up is informative but not the only viable option.

We can generalize the notions of interdependence here by defining distance in two ways. First there is the way in which agents move. Distance here defines how easily an agent can move from one task to another. This will be incorporated into the expectancy matrix Ω. In the KM example, this distance of motion is defined by the arc distance between any two states when they are projected onto a circle. Instead, more complicated relations could be defined here, indicating the difficulty of transitioning between any two states.

The other way to define distance is via proximity within an interdependence network. In the KM example, this second form of interdependence was established such that the proximity between any two states was defined by the straight-line chordal distance between the two states (when the states are projected onto a circle). Whereas the first distance was a distance of motion or transition, this distance is a distance of influence or attraction. While any matrix of non-negative values could be used to define a distance network, it is reasonable to use spectral clustering to estimate the distance of influence associated with a given interdependence network.

Let G be an interdependence network with positive weighted edges indicating pairs of tasks that are ideally performed together. I use the first two dimensions defined by the spectral decomposition of the graph Laplacian to define spectral positioning among the tasks. Distance is then defined by Euclidian distance between these spectral positions. Notably this is equivalent to what we did for KM when G is a circular graph.

The columns of V will be of the form:

$$V_{ij}[:,s] = re^{\frac{-(\psi_s - \psi_j)^2}{2\sigma_{SR}^2}} \tag{22}$$

Where ψ_s represents the spectral position of the s^{th} state. In some cases, instead of being driven to perform similar tasks, it is ideal to perform tasks as distal as possible. In such cases, the negative sign in front of the Euclidean spectral distance will be removed.

Multiple Interdependence networks may impact a team at one time. This can be modeled by defining additional V matrices that for the new dependency network. Specifically, it is very possible that while spectral proximity is ideal, it is best if teammates do not double up on the same task. In this case distance to one's self is defined as 0, and all other distances are set to some equal fixed number, and the negative sign is dropped. This leads to valence associated with not performing the same task as another agent.

A Priori Coordination Effort

The last step in building the network model of team coordination is to incorporate *a priori* coordination efforts. The KM is an entirely spontaneous model of synchronization, however, in interest of investigating the theoretical claims of this model regarding the differential effects of *in situ* and *a priori* coordination in various team contexts, it is important to explicitly incorporate a mechanism for *a priori* coordination.

This managed using a new matrix $P_i(t)$. Specifically, the $P_i(t)$ matrices columns are all identical. The established plan for who will do what and when can change over time. As with V and Ω there P is defined by variances, these control the level of precision in the plan. There are two different types of precision. Temporal precision controls how accurate the plan is regarding time. Secondly there is state precision which represents the ability of the plan to clearly distinguish between different states.

Simulations of the CSN Model

I have two main goals in the scope of this dissertation regarding this model. My first goal is to prove the equivalence of the network model with the KM. The purpose of proving this equivalence is to demonstrate the consistency of my proposed model with the existing literature, thereby demonstrating a level of credibility to an otherwise somewhat arbitrary formalization of the model.

With this goal completed, my remaining goal is to explore the implications of this model. In the remainder of this chapter, I will describe a set of simulation studies conducted and present the results. This dissertation then concludes with a discussion and future directions.

Overview of the Simulations

To explore the dynamic nature of feedback within the complexities of a network paradigm for understanding interdependence in the system, I simulated 16,000 teams with 6 agents each across 101 time steps (initial conditions and 100 simulated steps). Data were aggregated to the team level leaving 1,616,000 step-level observations.

Dependent Variable. The main dependent variable of the simulations was coordination. Technically, we measured a lack of coordination, defined as a Rayleigh Coefficient of the interdependent network (i.e. *G*) Laplacian matrix (i.e., call it *L*), and a vector $x(t)$. Where $x(t) \in \mathbb{R}^m, x = \sum_i x_i(t) - \frac{\text{sum}(x_i)}{m}$.

$$u = \frac{x^t L x}{x^t x} \tag{23}$$

This value (Equation 23) represents a sum of squared differences between any two nodes in the network *G* weighted by the strength of the edge between the given nodes. When team members are performing actions that support each other this coefficient will be high, and when team members are simply randomly performing tasks, this will be very low. To define coordination, *c*, we scale the negative of all simulated *u* values across the 1.6 million observations. A *c* value of 0 represents coordination that is average across all simulations, while a 1 represents one standard deviation above the mean level of coordination.

It should be noted that there are numerous alternative approaches to measuring coordination. Each has its own strengths, weaknesses, and theoretical nuances. The Rayleigh coefficient of the interdependence graph Laplacian most closely approximates my current use of coordination, but other applications may want to explore such parts as the correspondence measured as *r* in the equation for $\theta(x)$, or the Rayleigh coefficient of the graph adjacency matrix. As noted, the Laplacian approach provides clear theoretical meaning. However, one nuance of using this is that when multiple agents perform the same task this value is reduced, thus this operationalization of coordination does not count exact synchronization as coordination. In many cases, this may be appropriate, but in others, it is not.

Independent Variables. There are two primary independent variables of interest. First is social responsiveness. This is K as used previously in the equation for σ_{SR}^2. For the remainder of this chapter, I will use SR to label this value for interpretability reasons. As SR increases, agents will be more strongly influenced by other agents. From an expectancy theory perspective, this represents the valence associated with proximity (defined by the influence-based-distance metric) to other agents' states. Several parameters influence the scale and interpretation of SR. Perhaps most notably the value of σ_{ω}^{2} has a very direct impact on the way that SR functions. For this reason, exact values do not bear significant theoretical interpretation. However, based on previous work with the KM, it is reasonable to assume that SR ranges between 0 and 2. I allow it to go as high as 3 to illustrate what occurs in cases of extreme social responsiveness.

The second independent variable is *a priori* plan precision. As noted previously, the matrix P found in the model has precision in two ways. I use one factor that controls both types of precision. Essentially the precision term, *p*, controls the extent to which agents can distinguish between times as well as between individual tasks when attempting to follow a plan. The precision parameters (i.e., ρ_d and ρ_t) listed below are used as variances incorporated into an error function describing the agents' ability to distinguish states or time. These variances are both divided by *p*. Thus large values of *p* indicate cases where the agents can accurately distinguish times or states, while small *p* indicates cases where agents are worse at making such distinctions. See the Appendix for more details on the implementation. In the simulations run for this dissertation, *p* ranges from 0 (indicating that there is not an effect from *a priori* effort) and 10 (indicating a significant amount of *a priori* influence on tasks).

Moderators. A primary goal of the CSN model is to address the variable effect of *a priori* and *in situ* coordination under complex vs. simple and volatile vs. stable teamwork contexts. As such there are two primary moderators, each with two values creating a 2X2 design (4,000 teams in each cell).

First, complexity describes the complexity of the interdependence structure. The concept of interdependence network structures was established by Griffin and colleagues (2022a, 2022b). In this paradigm, interdependencies are thought of as relationships between tasks, people, roles, and resources defining how one's performance is impacted by others. In the simple case, interdependence is defined following a simple circular interdependence graph. This is analogous to the synchronization task described by the KM anddescribes a situation where tasks are clearly proximal (in which case you want to perform them at the same time) or not. There is little complexity; all you need to do is get as close to the same state as your teammates as possible and move with them. On the other hand, the complex case is defined by a randomly generated interdependence graph (with a density of .25). Managing interdependence in such a scenario effectively is much harder because each task a team member performs could have cascading consequences for their team members. Additionally, in the complex case, it is assumed that not only do team members want to perform tasks that aid each other, but there is a cost for having multiple agents performing the same task.

As noted previously, this paradigm is distinct from but compatible with prominent conceptualizations of interdependence (e.g., Courtright et al., 2015; Shiflett, 1972; Steiner, 1972). For example, sequential interdependence can be defined by defining interdependence relationships between tasks later in a sequence with outcome states of earlier tasks. For simplicity, I do not directly simulate a sequential interdependence structure, but could without significant effort.

Volatility is measured through changes in the P matrix. At each time point, there is a "perfect" plan established. This is defined by encouraging all members of the team to perform one of the tasks that correspond to either the largest n positive or smallest n negative value in the first eigenvector of the interdependence graph Laplacian. At any moment every agent is assigned a specific task to perform based on this criterion. Thus, the plan will promote coordination as defined by the Laplacian. In the low-volatility condition, P undergoes one shift from positive spectral positions to negative spectral positions. In the volatile condition, P undergoes 10 such shifts (each time, each agent is assigned a new task). Note that agents are not able to perfectly identify the plan as discussed previously. Their individually held beliefs regarding the *a priori* plan incorporates noise into this plan accounting for potential errors in timing precision, and potential errors where proximal tasks are mistaken for each other.

Table 3

Model Variables and Parameters of Interest

Name	Symbol	Value/ Range	Description
Independent Variables			
Social responsiveness	SR	[0,3]	Strength of *in situ* coordination efforts
Plan precision	p	[0,10]	Strength of *a priori* coordination efforts
Moderators			
Complexity	-	High/Low	Overall complexity of task interdependence. This is related to sensitivity to detail and cognitive load of coordination demands.
Volatility	-	High/Low	The extent to which task demands change frequently. This is related to the time scale of tasks and sensitivity to information decay.
General Simulation Parameters			
Number of Simulations	-	16,000	Total number of simulated teams
Number of agents	n	6	Number of agents in each team
Number of tasks/states	m	20	Number of tasks that team members chose among
Number of time steps	T	100	Number of time steps in each simulated team
Model Parameters			
Expectancy constant	σ_ω^2	.1	The variance in what tasks have a high expectancy
State precision	ρ_d	1	How well agents can distinguish between planned tasks
Temporal precision	ρ_t	12.5	How well agents can distinguish planned timing

Other Parameters of Interest. The CSN model incorporates various other parameters of interest. Due to the complexity of the model, interested readers are invited to look through the source code (Appendix C). With this said, I will list a few here worth noting in Table 3 below.

Results

Simulations of the CSN provide consistent support for the distinct temporal and density-based effects of *a priori* (e.g., planning) and *in situ* (e.g., social responsiveness) coordination efforts. The general pattern of results found from the simulations for each of four cases are described separately (i.e., High/Low Volatility X High/Low Task Complexity). After this more qualitative discussion, I provide a quantitative analysis demonstrating the distinct effects of temporal load and temporal stability of a team's performance context on coordination efforts.

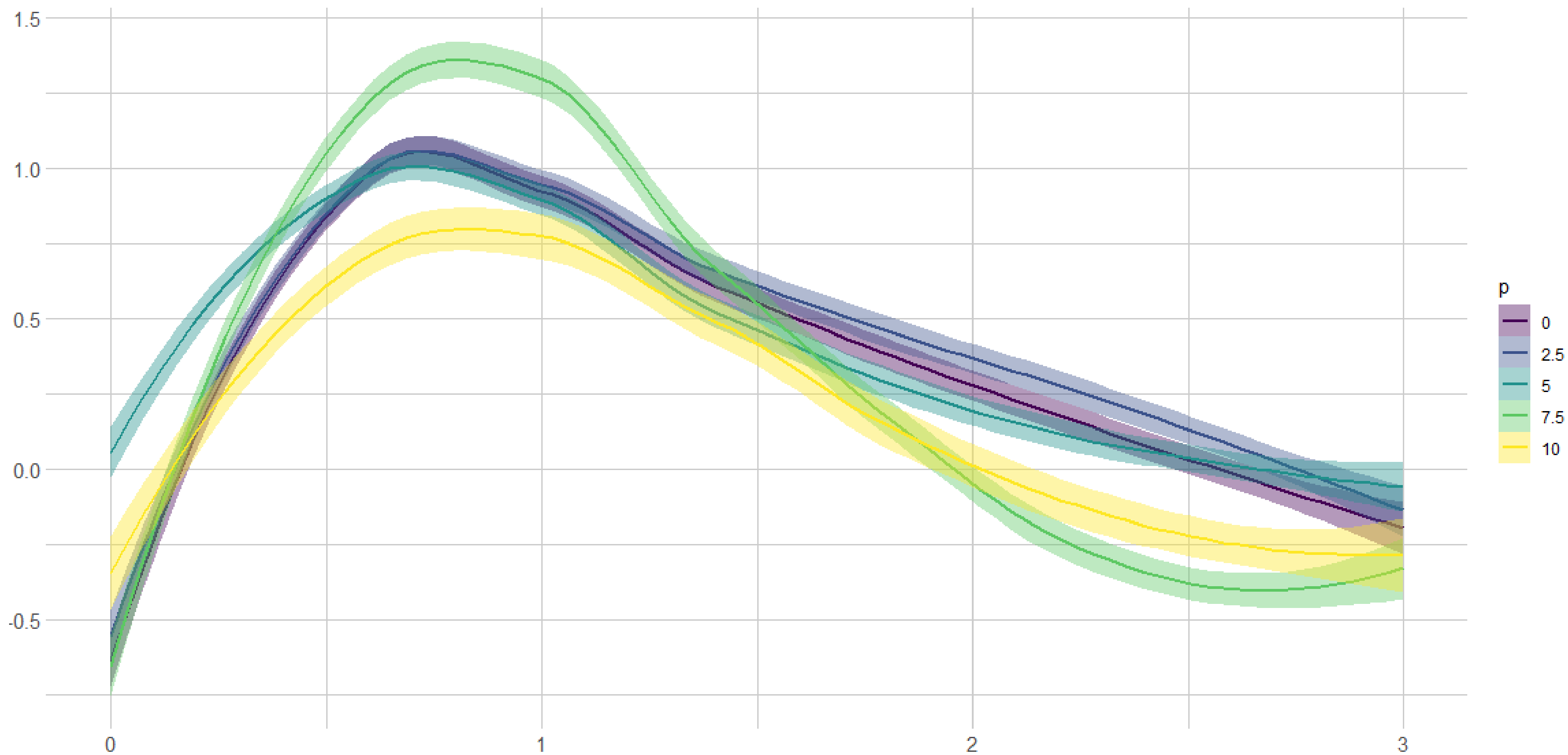
Notably, an SR score of greater than 1 represents agents being more influenced by others than by their own interests. As such, it is reasonable to consider SR > 1 as high, and SR > 2 as extremely high. The scale on *P* is dependent on simulation parameters, but for the sake of discussion, I refer to *P* = 10 as High *a priori*/planning efforts, 7.5 as Moderately-High, 5 as Moderate, etc. Coordination was standardized across the entire sample so that 0 represents average amounts of coordination compared to all other simulations, while 1 represents one standard deviation above the mean level of coordination.

Qualitative Analysis of Simulated Coordination Patterns

Simulations are grouped into four cases, based on High/Low Complexity X High/Low Volatility. Each of the figures presented below represents one case (e.g., High Complexity, Low Volatility), and presents the average observed levels of coordination (i.e., the DV represented on the vertical axis) for teams with various levels of social responsiveness (*in situ* coordination represented on the horizontal axis) and various levels of *a priori* planning/coordination efforts

Figure 15

Coordination in Low-Complexity, Low-Volatility Teams



Note. Lines indicate coordination levels for the average of 50 simulated teams. Each line is fit using a localized cubic spline. Colored shaded regions represent 95% confidence intervals for the population mean of teams at a given level of social responsiveness (horizontal axis) and planning (line color).

(represented through the color of a given line). Details regarding the operationalization and implementation of these factors can be found in Table 3 and Appendix C.

Low C-Low V. Results for Low Complexity, Low Volatility (Figure 15) indicate relatively little impact from planning, but clear non-linear impacts for social responsiveness. The finding is that moderately high levels of SR promote coordination in these simple contexts; however, further increased SR levels actually leads to a diminished level of coordination. This is likely due to the fact that such high consciousness of what the other agents are doing leads to switching without consideration of their own needs or what the others may do in the future. An example of such behavior is prevalent in the common occurrence of when two people walking in opposite directions both step in the same direction multiple times to get around each other in a hallway.[5]

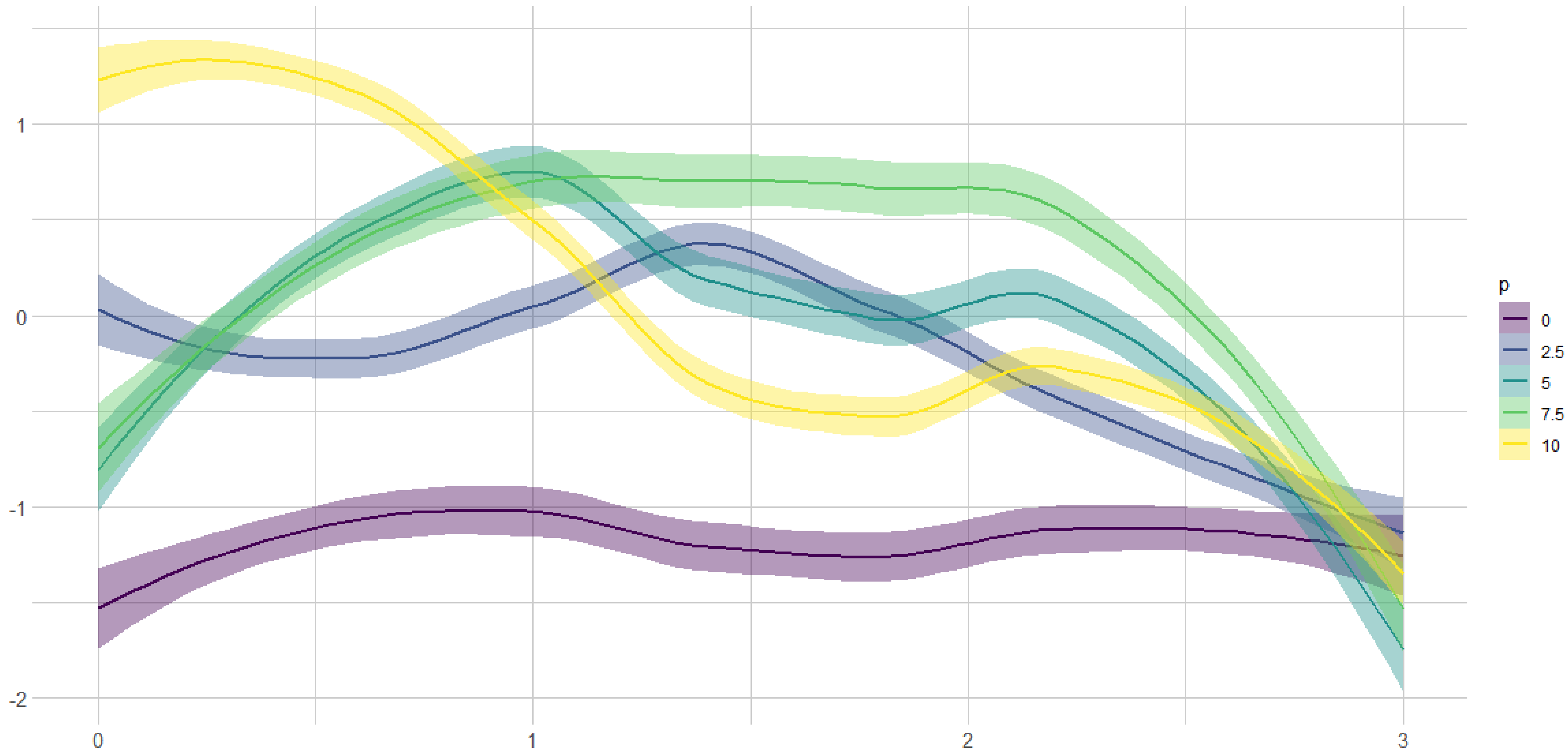
High C-Low V. Results for High Complexity, Low Volatility (Figure 16) are consistent with the theoretical predictions discussed previously. Specifically, *a priori* efforts appear to have more overall effect than *in situ* SR. For example, when P is 0 (the purple line), increases in SR have essentially no effect, whereas increases in P have clear and immediate positive effects on team coordination. In general, the more precision in planning the better. This is exactly what would be expected based on the theoretical discussion.

There are, additionally, more nuanced features of the simulated results which merit discussion. It is important to first recognize, however, that many of the features in

[5] Notably this effect is not present when using a different operationalization of coordination (for example the density radius); however such operationalizations of coordination are primarily applicable to the context defined by low task complexity, as defined here.

Figure 16

Coordination in High-Complexity, Low-Volatility Teams



Note. Lines indicate coordination levels for the average of 50 simulated teams. Each line is fit using a localized cubic spline. Colored shaded regions represent 95% confidence intervals for the population mean of teams at a given level of social responsiveness (horizontal axis) and planning (line color).

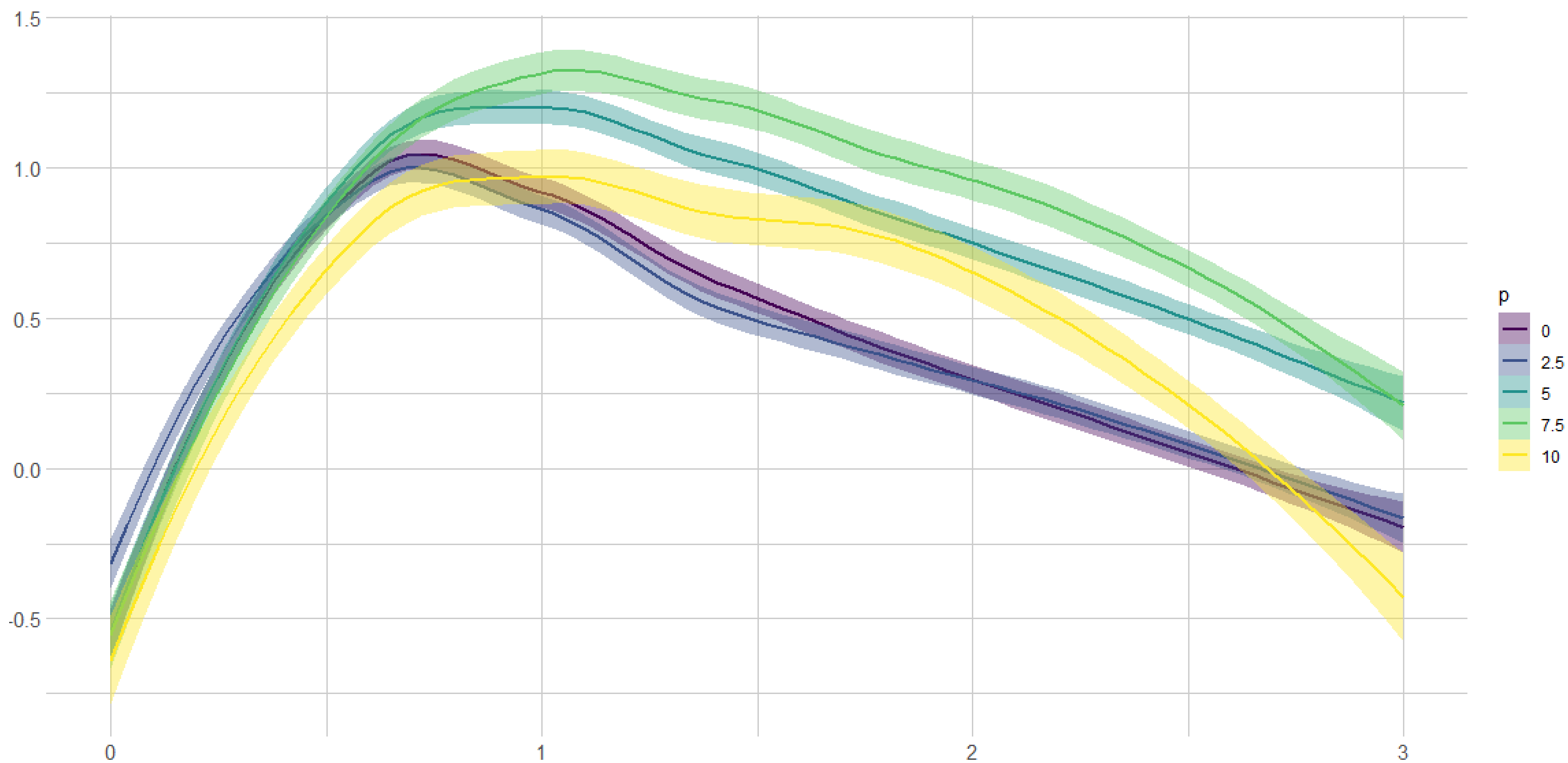
the simulated outcomes are likely artifacts of chance *P*; however, it appears that there is a general pattern where increased SR promotes coordination in teams with Moderately-High levels of (i.e., the green line), while increased SR leads to reduced coordination in teams with High levels of *P* (i.e., the yellow line). This suggests the theoretically important notion of interference, where strong levels of social responsiveness (SR) may mitigate the coordination benefits of planning. Future work will need to investigate this more.

Low C-High V. Results for high volatility contexts again were consistent with theoretical predictions discussed previously. Specifically, in highly volatile contexts social responsiveness is highly important overall, while *P* has inconsistent effects. In general, patterns are similar to the case with low complexity and low volatility where there is no clear if any *P*-effect, but a fairly clear SR effect. In fact, in the high volatility cases, this pattern is accentuated. For low to moderately high levels of SR, *P* has almost no apparent effect on coordination, whereas there is a clear positive strong effect of SR on coordination. Again, as SR becomes large there is clear simulated evidence of over-responsiveness where increased SR leads to reduced coordination.

Additionally, it appears that there may be a curvilinear effect for *P* on coordination when SR is high. This would suggest that teams working in simple but temporally volatile contexts will be less likely to experience the over-coordination phenomenon if they have moderate or moderately-high levels of *P* as opposed to very high or low levels of *P*. As mentioned previously, this “over-coordination” phenomenon is very dependent on the operationalization of coordination and disappears if you use the right coordination metric (See Appendix for details and comparisons of alternative operationalizations of coordination).

Figure 17

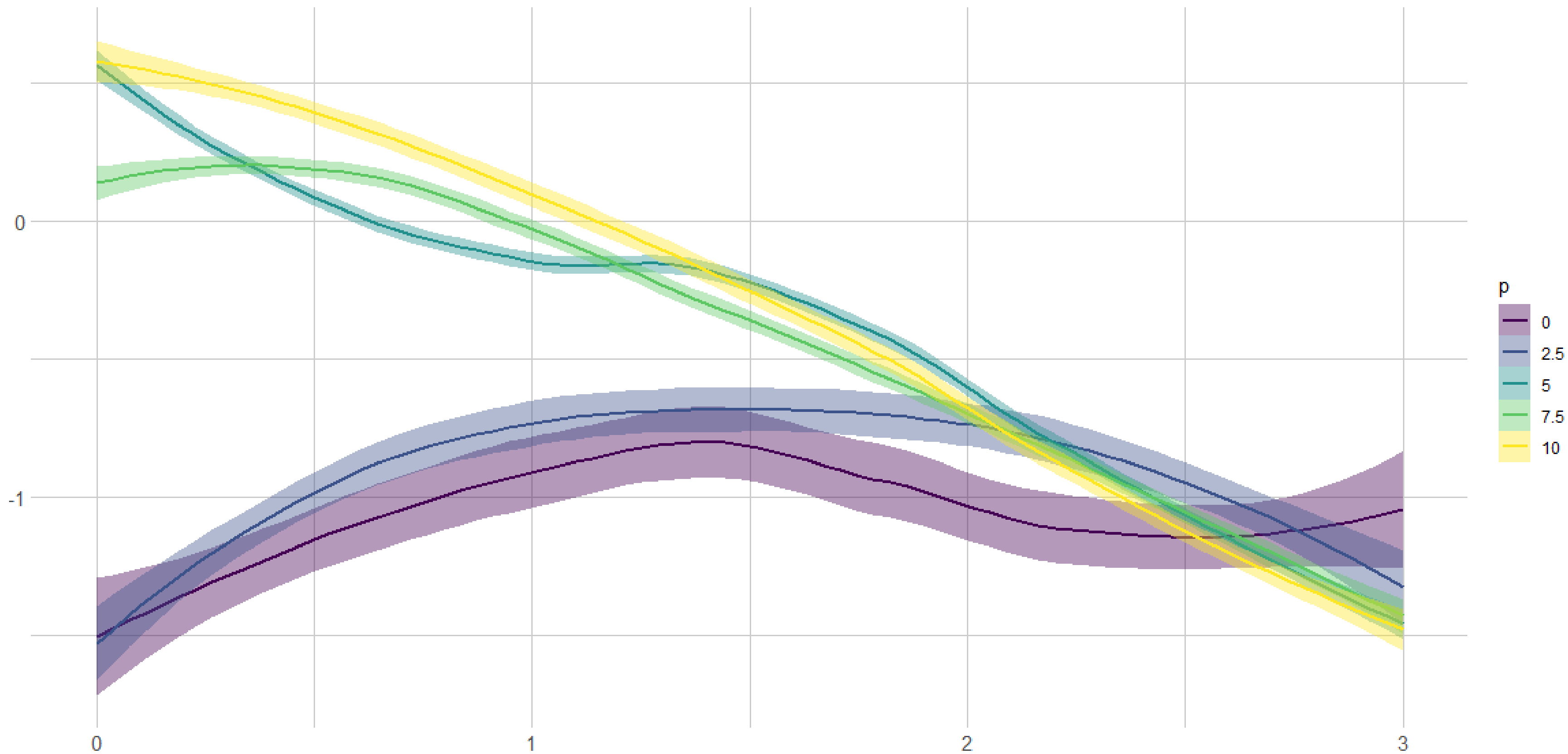
Coordination in Low-Complexity, High-Volatility Teams



Note. Lines indicate coordination levels for the average of 50 simulated teams. Each line is fit using a localized cubic spline. Colored shaded regions represent 95% confidence intervals for the population mean of teams at a given level of social responsiveness (horizontal-axis) and planning (line-color).

Figure 18

Coordination in High-Complexity, High-Volatility Teams



Note. Lines indicate coordination levels for the average of 50 simulated teams. Each line is fit using a localized cubic spline. Colored shaded regions represent 95% confidence intervals for the population mean of teams at a given level of social responsiveness (horizontal-axis) and planning (line-color).

High C-High V. While results for high complexity and high volatility are consistent with the information theory-based paradigm used for understanding coordination, this model does not explicitly describe what should be expected in the case of an interaction between high complexity and high volatility. Our results indicated a sort of pick one way or another but not both patterns.

For instance, in (Figure 18) there is a clear positive effect for SR (at least for moderate levels of SR) when *P* is low, and a clear negative effect for SR when *P* is high. Similarly, *P* has a clear positive impact on coordination when SR is low to moderately high, but very little effect when SR is high. Notably, coordination is optimized for low levels of SR and high levels of *P*. These simulations thus suggest the presence of an interaction where *P* and SR each have diminished effects as the other increases. The more socially responsive a team is, the less planning will help them, and the more they plan the less social responsiveness will help them coordinate in the context of these simulations.

Table 4

Regression Coefficients Predicting Coordination

	Low C – Low V b (SE)	**High C – Low V** b (SE)	**Low C – High V** b (SE)	**High C – High V** b (SE)
Intercept	-.152 (.043)	-.73 (.044)	-1.077 (.042)	-.209 (.042)
SR	1.268 (.054)	.628 (.056)	1.974 (.053)	.162 (.053)
SR^2	-.548 (.017)	-.298 (.018)	-.708 (.017)	-.207 (.017)
P	.042 (.013)	.271 (.014)	.164 (.013)	.19 (.013)
P^2	-.007 (.001)	-.017 (.001)	-.014 (.001)	-.009 (.001)

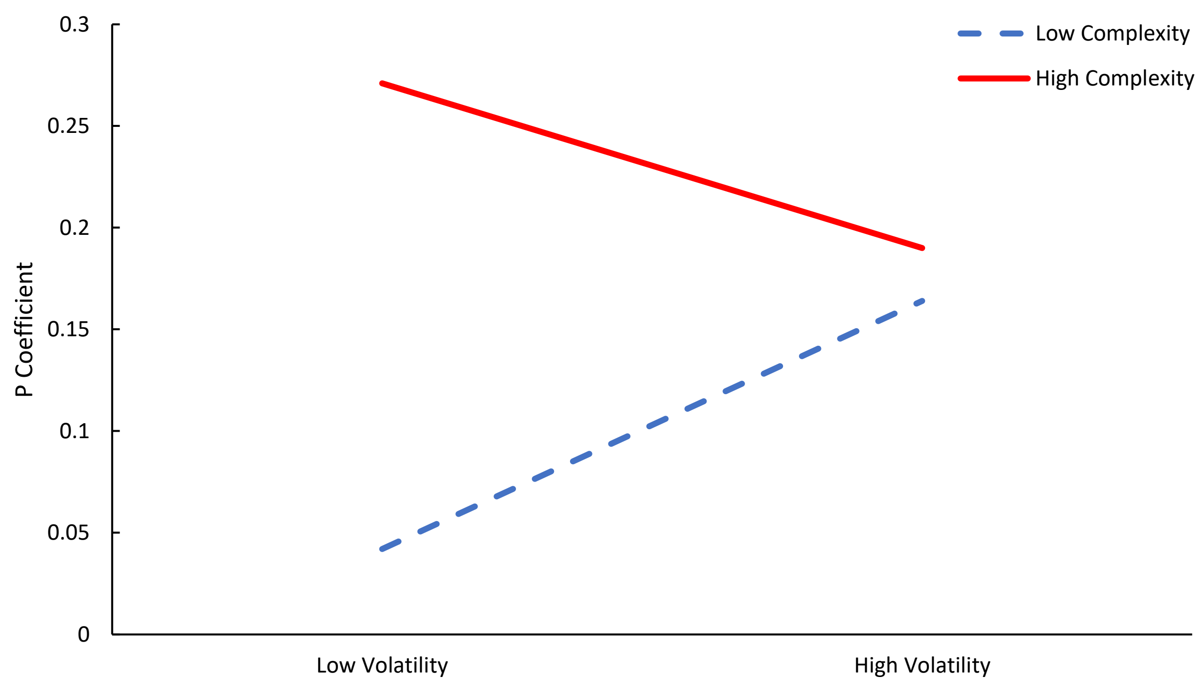
Note. Here, *b* represents unstandardized regression coefficients. C is for complexity and V is for volatility. Each model was identical but applied to data from different simulations (e.g., High Complexity, Low Volatility).

Regression Analysis

Using this same simulated team data, I regressed SR and *P* onto coordination for data collected from each of the four cases separately. Because coordination does not have an inherently interpretable scale, I standardized all coordination scores. Results are presented in Table 4. As seen in Figure 19, the *a priori* coordination efforts (e.g., planning) have a stronger impact on coordination in high-complexity team contexts situations vs. low-complexity contexts. This is seen from the fact that the line representing high complexity (solid red line) is higher than the line representing low complexity contexts (dashed blue line). Again, this provides support for the theorized relationship between *a priori* work and coordination in complex contexts.

Figure 19

Regression Coefficient of Planning on Team Coordination

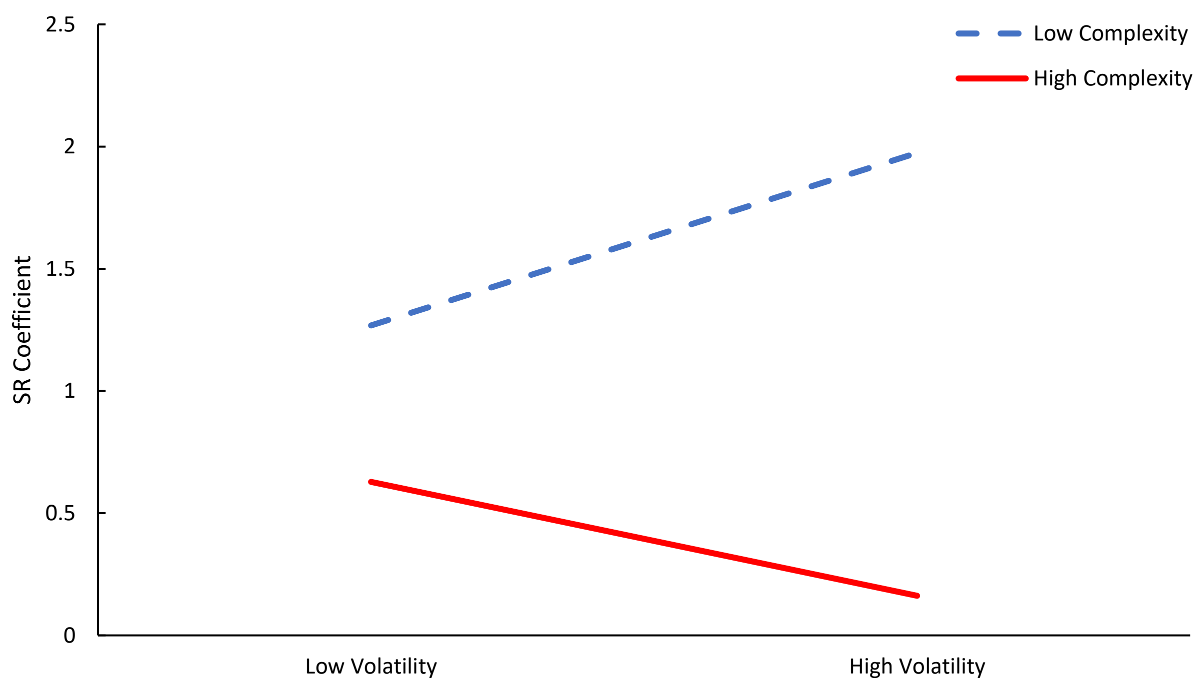


Note. The graph presents coefficients for *P* (i.e., *a priori* coordination effort) on team coordination controlling for P^2, SR, and SR^2. P ranges from 0 to 10.

There is mixed support for the relationship between contextual volatility and the importance of *in situ* coordination efforts. As demonstrated in Figure 20, SR has a stronger impact on coordination in volatile vs. stable contexts, but only when complexity is low. This is demonstrated by the positive slope for the low complexity contexts (blue-dashed line) in Figure 20. It should be noted that for high complexity, increased volatility leads to a diminished impact of SR (see the red line in Figure 20). This highlights the presence of an interaction relationship between complexity and volatility. This may also be partly explained by the fact that all predictors are generally weaker in high complexity, high volatility teams, as seen in Table 4. Regardless, SR has a very different impact on coordination depending on the level of complexity.

Figure 20

Regression Coefficient of Social Responsiveness on Team Coordination



Note. The graph presents coefficients for ST (i.e., *in situ* coordination effort) on team coordination controlling for SR^2, P, and P^2. *P* ranges from 0 to 3.

As a supplemental analysis, I ran a set of regression models that predict coordination as anteceded by *P*, P^2, SR, and SR^2, and included complexity and volatility as moderators. Results are presented in Table 5

Table 5

Regression Coefficients for Simulated Data

	Model 1: β (SE)	Model 2: β (SE)	Model 3: β (SE)
Intercept	.811 (.027)	.162 (.032)	.044 (.034)
SR	-.213 (.0122)	1.177 (.043)	1.177 (.043)
SR^2		-.463 (.014)	-.463 (.014)
P	.001 (.003)	.001 (.003)	.095 (.01)
P^2			-.009 (.001)
Complexity	-1.151 (.031)	-.895 (.037)	-.979 (.039)
SR	-.159 (.014)	-.707 (.05)	-.707 (.05)
SR^2		.183 (.016)	.183 (.016)
P	.099 (.004)	.099 (.003)	.167 (.012)
P^2			-.007 (.001)
Volatility	-.177 (.031)	-.127 (.037)	-.074 (.039)
SR	.056 (.014)	-.05 (.05)	-.05 (.05)
SR^2		.035 (.016)	.035 (.016)
P	-.001 (.004)	-.001 (.003)	-.044 (.012)
P^2			.004 (.001)

Note. Regression coefficients and their standard errors, for models predicting standardized coordination scores as an outcome.

Summary

The CSN model presented here has significant potential as a tool for exploring the implication of various facets of coordination in interdependent systems described by the CST framework. The CST paradigm provides valuable insights into the nature of coordination. Specifically, this model addresses the three limitations of coordination literature identified previously. First, this model explicitly incorporates social mechanisms driving the emergence of coordinated team action. This provides a clear perspective of how coordination processes are embedded within local team social contexts. Secondly, this model and simulations explicitly focus on the dynamic process of coordination, accounting for the important role of feedback and explicitly considering the trajectory of coordination in teams. Furthermore, the process-mechanism-oriented model can directly assess the theoretical implications of this work. As such, this work serves as a viable foundation for future empirical investigations into the mechanisms driving coordinated team behaviors. As with the previous model, there are several principles distilled from the results of the model.

Principles of the Model

The first principle is related to the concept of synchronization. Because the CSN is built upon an established model of synchronization (i.e., the Kuramoto Model), it brings with it a depth of information and a body of literature that is relevant to its interpretation. Although the equivalence of the proposed mathematical model is not strictly necessary for this to be a viable representation of the social-information theory-based paradigm of coordination process mechanisms, it provides valuable insight into the model.

The CSN model explicitly indicates a connection between synchronization and coordination. Perhaps most importantly, the model clarifies the distinction between the two concepts. Whereas synchronization implies doing the same thing at the same time, coordination implies doing the right thing at the right time. As such, coordination represents a closely related but much more complex concept than synchronization. Understanding the differences between these two concepts may have important theoretical and practical implications.

Principle 7: *Coordination is conceptually distinct from, yet closely related to, synchronization.*

Results from the simulations serve as a test of "generative sufficiently" and the logical consistency of the theorized information-based coordination process mechanisms. In particular, this work explicates the impact of complexity and volatility on *in situ* vs *a priori* coordination. This serves as a foundation for understanding the differences between these two types of coordination and the contextual features of teamwork that influence their differential impacts.

The results demonstrate the logical consistency of the theorized relationships. In particular, *in situ* coordination efforts in the model have a stronger impact on team coordination outcomes for highly volatile teamwork contexts. Similarly, *a priori* coordination efforts have a stronger impact on team coordination efforts for simulated teams in highly complex work contexts.

Principle 8: *Complex work contexts are more strongly impacted by a priori coordination efforts than simple work contexts.*

Principle 9: *Volatile work contexts are more strongly impacted by in situ coordination efforts than stable work contexts.*

Consistently, results indicated that *in situ* efforts generally lead to increased levels of coordination as was predicted. But somewhat counterintuitively, this effect was only consistently found in low-complexity team contexts. Furthermore, this effect experiences diminishing returns as *in situ* efforts increase. In fact, when social responsiveness increases from strong to very strong, overall levels of coordination appear to diminish in each of the simulated conditions.

Notably, teams that have both highly complex and volatile tasks appear to have an interaction in the impact of *a priori* and *in situ* coordination. In particular, teams with a high degree of *a priori* coordination do not appear to benefit from a high degree of *in situ* coordination effort.

These results suggest that teams can be too socially responsive, particularly in highly complex contexts. While perhaps counterintuitive at first, there are contexts where this makes sense. For example, teams that spend too much effort thinking about what the other person is doing may fail to account for their own task needs. Also, individuals driven to perform tasks that relate to their teammate's task may end up duplicating effort. For instance, in teams where there is an extremely high level of responsiveness, slight changes in teammate's actions necessary to accommodate a team's plan could be responded to in an amplified way by teammates. This could lead to a positive feedback loop where the original team member adjusts their efforts even more drastically. While such cyclical, reactive behavior may be intended to lead to highly coordinated action, it is unlikely to do so in an effective way. As such, a more moderate level of social responsiveness may be ideal for enabling a team to incorporate and respond to new information within an action phase without over-responding. When a team is too socially responsive, the team members could possibly neglect their own initial responsibilities while making seemingly small natural adjustments to a team's working strategy.

The results of this simulation do not prove that over-coordination is something that occurs in teams, it simply presents evidence that the mechanisms discussed in this coordination framework are sufficient to create this effect. Moreover, it is important to note that these results, as with all simulated results, are parameter-specific. Additionally, these results depend significantly on the definition/operationalization of coordination used. Regardless, the results generally indicate that moderately high levels of social responsiveness are positive, but there is little need to put effort into further increasing social responsiveness to avoid these levels. This further demonstrates how the formalized theories can point to relevant but initially counterintuitive concepts.

Principle 10: *Social responsiveness leads to increased coordination in teams with relatively simple task interdependence structures.*

Principle 11: *Positive effects of social responsiveness experience diminishing returns such that, in general, moderately high levels of social responsiveness lead to maximal levels of coordination. Extreme levels of social responsiveness may lead to over-reactivity that leads to a reduced level of coordination.*

Limitations

Results from these simulations are highly dependent on the parameters used and the specific operationalization of coordination as well as complexity and volatility. Thus, although the results are consistent with the theories' expectations, this is likely, at least in part, dependent on these various operationalizations. The operationalization of coordination used here has some specific implications. Coordination as operationally defined here explicitly treats performance of the same task by multiple people as duplicated effort, not coordination. This implies a preference for an even spread of effort allocation. While duplicated effort may be performant in some cases, in many cases multiple tasks must be performed together. For this reason I opted to use this operationalization of coordination. It should be noted that this choice is likely to have amplified the "over-coordination" effect found in the simulations. While the results cannot be completely explained by this operational choice, future work investigating various operationalizations of coordination should be used to evaluate how robust the over-coordination findings are.

Another significant theoretical issue is that these simulations do not adequately account for the need teams have for the ability to adapt to unexpected events. In high complexity and high volatility, teams that have strong *a priori* coordination efforts, and no *in situ* coordinated efforts demonstrate maximized coordinated action. In other words, these teams did the best job at coordinating when they performed tasks ignorant of what their teammates were doing at that moment. This makes sense for conditions where the volatility the team tasks experience is predictable (as is the case in these simulations). It may be more appropriate to operationalize volatility in an unpredictable manner. This would lead to the strict observance of *a priori* plans to potentially be problematic if teams have no ability to respond to the unpredicted changes in their teammate's needs. Future extensions to this model should account for random shocks to the team's systems, and other sources of unpredictability. For example, simulations that incorporate sudden changes to the team's work system, team membership, or the external context could provide insight not only into how effective teams are, but also how adaptable they are. It is expected that even in contexts where results suggested *a priori* coordination was more important than *in situ* for team effectiveness, teams should have a healthy level of responsiveness to effectively adapt. While not trivial, such simulations would be a straight-forward next step in this research stream.

This model underscores the same important factors of coordination that the team-level model did. Specifically, it highlights the informational and motivational processes driving individuals to coordinate. It does so from a dynamic perspective, clearly and explicitly incorporating the localized embeddedness of each individual within their team context. Further, this model highlights the importance of social factors in driving individual responsiveness to others and enabling teamwide coordinated effort. Another point to make is that while this model is largely conceptual at this point, it has significant potential as an applied tool for modeling the impact of different environmental factors, contextual factors, and policy decisions on a team's ability to coordinate.

Discussion

Never doubt that a small group of thoughtful, committed people can change the world. Indeed. It is the only thing that ever has.

— Margaret Mead

Overview

This dissertation lays a foundation for understanding and defining the process mechanisms of coordination in a team from a dynamic multi-level perspective. Building on this conceptual foundation, I specifically provided a detailed description of the socially embedded process mechanisms of emergent coordination in teams and organize this into the Coordination Signals Theory (CST) framework. Furthermore, this work specifically highlights a signal exchange/feedback process that can make coordination a synergistically amplified phenomenon and elucidates the distinction between two different forms of coordination efforts and their differential impacts on a team's realized coordination.

This dissertation contributes to the coordination literature by presenting the CST from an information theory-based paradigm underscoring the informational mechanisms of coordination that have thus far been largely overlooked. This informational perspective provides a unique and powerful way to characterize the coordination demands of various work contexts in terms of detail and time sensitivity. Although these contextual elements of work in teams likely play a critical role in determining coordination processes, little work has addressed these concepts, particularly in a way that addresses the dynamic nature of coordination.

Moreover, the proposed CST includes two formal mathematical models. The first, the CASER model, is a dynamic systems model considering coordination from an aggregated team-level perspective. This model identifies a qualitative pattern of socially amplified coordination through mechanisms of informational feedback. Results from the analysis of this model provide clarity regarding the differential impacts of *in situ* and *a priori* coordination efforts on coordination signals. Of particular importance, this first model provides significant insight into the potential role of dynamic feedback in generating sustained team coordination. Each of these constitutes a unique contribution to the coordination literature.

The CSN (i.e., the second model) presents a network-based perspective of coordination processes. This extends the work of the CASER model to account for the locally embedded nature of coordination in a team. This second CSN model provides further detail and insight into the potential social-informational process mechanisms driving the emergence of coordinated actions within teams. This work allows us to consider differences in task ability/assignment, as well as differences in interdependence structures and social structures. Results of study two provide a clear demonstration of the logical consistency of the theorized impacts of both *in situ* and *a priori* coordination, which have the potential to inform us of conditions wherein various coordination processes will break down, and when coordination is particularly effective. This work has highlighted various mechanisms and perspectives on how coordination occurs. Even if these are inaccurate, its contribution is to present formally defined mechanisms that can more clearly be represented and tested in future empirical work.

The CSN had two parts. First, I derived the model as a discrete generalization of the Kuramoto model. This demonstrates the consistency of the model with existing approaches to studying collective synchronous behaviors. Having established the approximate equivalence, the next step is to conduct a simulation study. The simulations vary the level of complexity and volatility as well as factors representing *in situ* and *a priori* coordination. Results provide support for the conceptual viability of this social-information paradigm. In addition, this establishes a tool for further studying the dynamic, socially-embedded nature of coordination.

Table 6

Principles From Model Results

#	Model	Proposition
1	CASER	*Coordination in a team will generally follow a dynamic equilibrium trajectory, approaching some steady level of coordination within a team.*
2	CASER	*When a team establishes a strong level of coupling (i.e., social responsiveness - effectively generates signals and cues regarding each other's activities, and actively responds to these signals) relative to the decay rate of information, the team will exhibit a non-trivial, steady level of coordination. The greater the coupling, the larger the steady level of coordination in the team.*
3	CASER	*Teams exposed to some form of external coordination cues, or that have some inherent force driving coordination, in the absence of* in situ *cues will exhibit a non-trivial, steady level of coordination. The stronger such external influences, the larger the steady level of coordination will be.*
4	CASER	*Holding the stability of the ready state constant, a team's steady level of coordination will be augmented as the stability of coordination information and signal is increased.*
5	CASER	*Coordination will generally lead to increased performance. This is dependent on the level of interdependence of the team (more interdependence means stronger relationships between coordination and performance), and the process inefficiencies associated with coordination.*
6	CASER	*Feedback is an essential driver of the impact of coordination, and a determinant of a team's ability to establish a steady amplified level of coordinated effort.*
7	CSN	*Coordination is conceptually distinct from, yet closely related to synchronization.*
8	CSN	*Complex work contexts are more strongly impacted by a priori coordination efforts than simple work contexts.*
9	CSN	*Volatile work contexts are more strongly impacted by in situ coordination efforts than stable work contexts.*
10	CSN	*Social responsiveness leads to increased coordination in teams with relatively simple task interdependence structures.*
11	CSN	*Positive effects of social responsiveness experience diminishing returns such that in general moderately high levels of social responsiveness lead to maximal levels of coordination.*

Practical Implications

There are numerous practical implications for this work. First, by explicating the differences between *in situ* and *a priori* coordination, the CST points to distinct routes of intervention that practitioners and organizations can leverage to improve team coordination and augment performance. Specifically for teams that are in informationally loaded contexts where work is complex and tasks require significant amounts of detail to complete, this work suggests that effort focused on individual mental model development will be highly impactful. In such cases focusing too much on learning what one's teammates are doing and the relationship between the roles of different members of the team by be counterproductive as it adds noise to an already cognitively loaded task. Relational model development would still be important, but this computational study and theory indicate that the priority should be to facilitate individuals learning their specific roles and tasks.

On the other hand, when tasks switch frequently, and the team experiences high levels of volatility, the rigidity of *a priori* coordination which is characterized by this individual mental model development, can become a liability. Thus, in highly volatile conditions, the results of this work suggest that teams would benefit from efforts to better facilitate socially responsive task performance. Such efforts include increasing the ease of communication between team members and encouraging team members to put more effort into communication. This also would include work during transition phases to augment relational mental models that enable team members to understand how their work impacts and is reliant on the work of other members of the team. As in the reverse case, the individual mental model developmental focus of *a priori* coordination is still important in such cases, but this theoretical framework and the simulations suggest that a greater emphasis needs to be placed on relational model development in volatile team contexts.

Although these results are theoretical, they provide a clear justification for the generative sufficiency of the CASER and the CSN models. That is, this work demonstrates that the theoretical CST framework presented in this dissertation provides sufficient logical grounding for the proposed relationship between complexity/volatility and *in situ/a priori* coordination efforts. As such it provides a powerful groundwork to build upon for future empirical and applied research. This work has tremendous potential to augment our understanding of coordination and inform coordination-focused intervention.

In addition to general principles that could be applied to work situations, the CST presents a foundation for understanding and augmenting coordination in human-machine teams (HMT). Although psychologists and organizational scientists have studied psychological processes impacting individual reactions to computer agent team members, this work is primarily on the level of individuals' perceptions. This dissertation provides a way to understand the complexity of the socially embedded processes of coordination which may play an important practical role in enabling humans to respond to and signal computer agent team members more effectively. Similarly, computer scientists have put significant effort into enabling computer agent team members to interface well with humans. This is clearly evident in recent advances (e.g., ChatGPT). However, thus far this work is primarily focused on predictive models used to interpret explicit human signals. The framework presented in this dissertation possibly provides a route to enable computerized agent team members to symbolically encode their place within the team's interdependent processes and proactively perform tasks in a way that better responds to the needs of human counterparts.

Limitations and Future Work

A significant limitation of this work is that it is simulation based. This is a powerful tool to develop theory, make predictions, and explore implications, but it is not empirical. As such, all results and propositions are demonstrably consistent with the CST, but future work will need to empirically validate these findings. This future research will incorporate various measurement-related tasks. For instance, work is needed that will establish clear ways of distinguishing the complexity and volatility of teamwork contexts. As part of this work, it would be valuable to investigate various interdependence structures and their impacts. Further empirical research is also needed which investigates the role of information-sharing processes on coordination processes. These future empirical studies will also need to clarify differences between planning efforts aimed at development of individual vs. relational mental models.

Another limitation of this work is that it does not directly address performance. Instead, it is focused entirely on the emergence of coordination. Other work has conceptually investigated the connection between interdependence and performance (Griffin, Somaraju, Olenick, et al., 2022), but future work will need to explicitly connect these two concepts clarifying the role that factors promoting coordination play in team performance outcomes.

As a final note, one area where these concepts and contributions are of particular importance is in human-machine teams (HMT). With the advent of advanced machine learning tools, machines are treated more as an autonomous members of a team – with their own roles, goals, and responsibilities – than simply as a tool used by human team members (Flathmann et al., 2019; C. D. Johnson et al., 2020; M. Johnson et al., 2012; Laengle et al., 1997; Schelble et al., 2022; Scheutz et al., 2017). This trend is prevalent in manufacturing (Flathmann et al., 2019), medical (Nourjou et al., 2011; van der Waa et al., 2021), transportation (Hussain & Zeadally, 2018), and military applications (Lin et al., 2008; Marchant et al., 2011), and will only expand further with technological advancements. Such HMTs have significant challenges that make coordination difficult because in many cases humans either do not trust or do not know how to properly integrate with autonomous machine team members. Similarly, machine learning algorithms utilized by autonomous machine team members are typically designed to perform a specific function, not to integrate cohesively within a complex social team context. By providing a rigorous theoretical framework for the concept of synergy and further providing a formal language from which to discuss these concepts, this dissertation is providing a critical bridge that could be used to facilitate the development of cohesive teamwork in HMTs. Thus, in addition to significant theoretical applications, this dissertation will lay an important practical foundation from which to approach resolving fundamental difficulties faced by integrated HMT's. Future applications of this work will leverage it as a tool for augmenting coordination in HMT's.

Conclusion

Coordination is a critical part of work in teams, yet our existing understanding of coordination has major limitations. This dissertation presents the Coordination Signal Theory which expands the team coordination literature by providing a dynamic, social-embedded, and process-mechanism-oriented understanding of coordination. It uses two distinct yet complementary formal models (i.e., the CASER and the CSN model) to provide unique and novel insights into the nature of coordination. This work theory provides substantial conceptual developments and establishes a groundwork of process-mechanism-oriented theories capable of supporting future coordination research.

Not only does the CST framework provide critical theoretical advances to our understanding of coordination, but it also provides crucial practitioner-oriented insights into interventions that could augment team coordination. As work in teams gets more complex and fast-paced, such work has the potential to play a powerful role. Specifically, the advent and spread of human-machine teams suggests the clear potential and importance of this work.

I submit that the CST and its accompanying formal models establish a groundwork that allows us to understand more clearly the beautiful nuance of how teams can coordinate in orchestral harmony. This elucidates concepts such as rehearsed (*a priori*) and unrehearsed (*in situ*) coordination. This work lays the groundwork for substantial advances in understanding and improving team coordination processes.

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APPENDIX A: COORDINATION AND THE ANALOGY OF A LASER

To motivate a deeper dive into the nature, impact, and function of coordination in a team on the level of process mechanisms, it is valuable to consider these concepts from a broader perspective first. To understand the impact of coordination, it is informative to consider the example of cohesive light found in a LASER. Specifically LASERs exemplify the value and impact of highly coordinated or synchronized systems in amplifying the effectiveness of the system. This serves as an excellent framework from which to approach an investigation of the emergent nature of team-performance amplification through coordinated effort. In the following section I will use the analogy of a LASER to illustrate the potential for coordination to act as a catalyst for synergistic performance application within a team. I first present a brief overview of how LASERs work, then present a theoretical discussion of how this is analogous to teams. This analogy is presented on a team level illustrating the function of coordination on the aggregate, laying the theoretical groundwork for understanding the more mechanistic network-based perspective that follows.

Notably there are two primary ways I hypothesize that teams will be able to cause social application of performance: Coordination and Motivation. Though motivational processes have various similarities to LASER, the analogy is leveraged primarily to discuss social mechanisms of performance amplification through emergent coordination behaviors. Thus the focus of this section is to lay a groundwork for understanding how due to interdependencies among team member's tasks, coordinated effort can allow teams to facilitate each other (or at least minimize interference) maximizing the effectiveness of the effort while minimizing process losses. Motivational routes for potential social facilitation of team performance are touched on here, but only briefly. They are discussed in greater de later on in this dissertation.

Overview of a LASER

Light Amplification by the Stimulated Emission of Radiation (LASER) is a process by which light is crafted into a single beam of same-frequency, in-phase light flowing in the exact same direction. Notably, the total amount of energy within a LASER's single beam of cohesive light is not necessarily any greater than the amount of energy released from another light source (e.g., a lamp). This highlights a misconception often associated with LASERs. LASERs are more powerful than nonlasing light sources, not because of the total energy, but because of the precision of that energy. To tie this to a popular work adage, LASERs, "work smarter, not harder".

In a team's work context, it is well known that interdependency among tasks can lead to process loss, where efforts misalign, are duplicated, or are overlooked due to the interdependent work environment (A. Espinosa et al., 2002; Steiner, 1972). This is a main theoretical justification for the importance of coordination within teams; teams that coordinate effectively outperform teams that do not; this is particularly true in highly interdependent work contexts. Returning to the LASER analogy then, we can think of a LASER as a light source that compels it's light to be highly coordinated. In fact, the physics term for this is *cohesive light*, which points to the team notion of cohesion and coordination well. If we can get a team to act in a way similar to how a LASER functions so that their efforts are highly cohesive and coordinated, it is possible that we will see dramatic amplification of team performance. Thus, the way in which a LASER works provides useful insight as to ways we can potentially enhance team functioning. Specifically, the LASER analogy provides a theoretical model of social facilitation potentially capable of greatly enhancing team performance. Diving into the analogy deeper, there are three primary components of a LASER, and three physical processes that enable a LASER to function, each analogous to a factor phenomenon of work in a team.

Processes Necessary for LASERs

There are three core mechanisms that allow a LASER to function. These are 1) *absorption*, 2) *spontaneous emission*, and 3) *stimulated emission*. Absorption describes how a substance that is exposed to energy absorbs it. Spontaneous emission is the process by which energy already absorbed by a substance is released in the form of light energy. It is spontaneous because an energized substance will release its energy in the form of light on its own without any external stimulus. The resulting light will be released in a random direction at a random time. This is the process that produces most light we experience, whether in a campfire, an electric lamp, an LED, or a stovetop.

While these first two processes are sufficient to generate light, LASER-action (the term for the positive feedback loop that is responsible for the generation of cohesive light in a LASER) requires a third process: stimulated emission. When a substance is energized, there is a brief period before it releases its energy in the form of light. If energized material is struck by compatible light, it will immediately send out an identical ray of light. Therefore, the emission of light is stimulated by an existing ray of light and is not spontaneous. Unlike the random nature of spontaneously emitted light, light emitted via stimulation is cohesive, a fact that is responsible for the unique characteristics of LASERs.

Components of a LASER

Further extending this analogy, consider the three primary components essential to generating a LASER. These are 1) the *pump*, 2) the *LASER medium*, and 3) the *optical chamber*.

We can think of these components as the motivators, the team members, and the team's work context respectively.

The LASER Medium. LASER medium is the substance that absorbs and subsequently releases energy in the form of light. In our analogy, these are the members of the team. Importantly, for a LASER to form, the medium must have certain characteristics. First, it must be uniform. For example, impurities in a ruby LASER will dramatically inhibit its ability to generate a cohesive beam of light. The primary issue here is that slight discrepancies lead to differences in the nature of light produced by the material. This in turn inhibits the process of stimulated emission. A second important characteristic of the LASER medium is the need for it to have a semi-stable energized state. When the medium is excited, it doesn't immediately convert the input energy into light output; instead, it is able to hold onto the energy long enough to encounter light emitted elsewhere and thereby produce stimulated cohesive light. If the medium does not remain in an energized state long enough, there will be no chance for stimulated emission, and therefore a cohesive beam of light cannot be generated.

The Optical Chamber. The second component necessary for a LASER is the optical chamber. This is where the LASER medium is stored, and where everything takes place. It is analogous to the team's work context. There are two characteristics of the optical chamber crucial to generating a cohesive light. First, the optical chamber is fitted with parallel mirrors on either end. This enables light emitted by the LASER medium to be reflected back into itself, thereby providing more opportunities for stimulated emission of light that happens to be going in the right direction. Without this, energy would dissipate from the material at too fast a rate for LASER-action to ever occur. The second characteristic of the optical chamber of note is its precise dimensions. An optical chamber is designed to be exactly some whole number times the wavelength of the emitted light. This enables the optical chamber to sustain a standing wave, maximizing the cohesive nature of a light emitted from a LASER.

The Pump. In a LASER, the pump is the source of energy that is subsequently converted into light. Without some source of energy, a LASER will not turn on. Additionally, the performance of the LASER is closely tied to the consistency and strength of the energy pump. Weak and inconsistent sources of energy will lead to faltering LASER-action.

A core concept to this is that cohesive work, such as in light produced by a LASER, is a far more effective tool than randomly dispersed work (e.g., a random light source). This notion applies directly to the study of teams. Researchers have found, for example, that coordinated effort is far more effective than uncoordinated effort (DeChurch & Mesmer-Magnus, 2010a; Rico et al., 2008). This is particularly true in highly interdependent work settings, where effort from one team member may greatly facilitate or inhibit the efforts of other team members (A. Espinosa et al., 2002). Coordinated effort toward a single clear goal will be far more effective than the same amount of effort allocated toward individual goals. Building on this foundational research, I use the perspective of how a LASER functions to provide a window into the underlying dynamic emergent processes of coordination and synchronization in a team.

The process and components of a LASER are described in Table 7 they provide a powerful analogy and perspective for understanding a dynamic, emergent process of coordination that can be applied to understanding teams. In the following sections, I extensively rely on this analogy; however, only a simplistic understanding of the processes driving a LASER to function, as presented in Table 7 is necessary to understand the broader theoretical concepts herein described.

Table 7

Mechanism and Components of Team Coordination and Correspondence to LASER

	Teamwork		*LASER*	
	Name	**Description**	**Name**	**Description**
Mechanisms				
	Motivational Internalization	Individuals put into a motivated "ready state"	Stimulated Absorption	Elections put in semi-stable energized state
	Spontaneous Effort	Individuals act according to internal objectives	Spontaneous Emission	Electrons drop to lower state spontaneously releasing photon
	Stimulated Coordination	Individuals act in coordinated way based on coordination signal	Stimulated Emission	Energized elections struck by photon and releases cohesive photon
Components				
	Motivator	Source of motivation - Must be strong enough t reach level of population inversion	Pump	Source of initial energy - Must be strong enough to reach level of population inversion
	Team Members	The people being motivated - Must have reasonable level of social responsiveness - Must be capable of compatible work	Laser Medium	The substance being energized - Must have semi-stable energized state - Must produce cohesive light
	Work Context	Place where motivational coordination process occurs - Facilitate exposure to each other - Facilitate timing in a way that amplifies effort	Optical Chamber	Chamber designed to hold standing LASER wave - Designed to internally maintain beam - Built precisely to facilitate standing wave

APPENDIX B: NONDIMENSIONALIZATION

To nondimensionalize a model we apply transformations to each stock variable, as well as time itself. These transformations remove the "characteristic units", producing dimensionless variables. This technique is particularly valuable when we do not have theoretical values to put in for each of the values and are more interested in describing general patterns of behavior than specific observed patterns. In essence, although very mathematical, this technique applied here should be interpreted more qualitatively than quantitatively, as the values represent general concepts and not actual observed values. This technique is also a powerful tool for identifying qualitative patterns while reducing the total number of parameters required to fully parameterize a model.

We set dimensionless variables for time (τ), ready state (ρ), coordination signal (γ), and work (ω), and define characteristic units (t_c, R_c, S_c, and W_c) as follows.

$$t = t_c\tau$$

$$R = R_c\rho$$

$$S = S_c\gamma$$

$$W = W_c\omega$$

Applying these transformations to Equations 1, 2b, and 3 gives us the following system of equations:

$$\frac{d\rho}{d\tau} = \frac{t_c}{R_c}m - t_c S_c k\rho\gamma - t_c l_R \rho$$

$$\frac{d\gamma}{d\tau} = \frac{t_c}{S_c}p + t_c R_c k\rho\gamma - t_c l_S \gamma$$

$$\frac{d\omega}{d\tau} = \frac{t_c R_c}{W_c}\beta_u l_R \rho + \frac{t_c R_c S_c}{W_c}\beta_c k\rho\gamma$$

This is simplified by setting appropriate characteristic units. Note that this can be done atheoretically by simply assigning characteristic units which best simplify the system. However, for pedagogical purposes, as well as to more clearly tie this work to psychological theory, we will provide theoretical rationale for the characteristic units being used where possible.

First, we assign a characteristic unit for time, t_c. In this case we will let time be defined by the decay rate of the ready state. In doing so, we will define a dimensionless system where time is characterized by the stability of the team member's ready state. Note that this is consistent with the work of Simon and Ando, which clarifies the effects of times scales on psychological processes (Simon & Ando, 1961). By setting the characteristic unit in this way, in effect, we establish the timescale at which the ready state changes as the primary time scale of the system. Anything occurring much faster than this time scale will appear to occur nearly instantaneously from this paradigm, and anything occurring much slower will appear to be static. While this system can be used to evaluate changes in this rate (e.g., possibly an intervention will increase the responsiveness of individuals to coordination signals) this choice makes it easiest to treat this decay rate (level of instability in the ready state) as a constant. From an atheoretical perspective, we simply set the final coefficient in Equation 1 to a unitary value.

$$t_c = \frac{1}{l_R}$$

Next, we assign a characteristic unit for the ready state variable, R_c. Here we note that the system has a constant input value, m, defined by the motivational strength of the system. We can therefore define a characteristic unit for R that is relative to this value. However, m is a rate and so we will need to scale this value by the time characteristic unit. From an atheoretical perspective we are simply unitizing the first coefficient in Equation 1:

$$R_c = mt_c = \frac{m}{l_R}$$

Now we must assign a characteristic unit for the coordination signal. It is reasonable and possible to set this in relation to the direct coordination signal strength, p; however, we will want to investigate cases where p is trivial, or 0. With this in mind, it is a poor value to use as the basis of a characteristic unit. Instead, we will use the rate at which ready state individuals perform coordinated work (i.e., kRS). While there are multiple ways to set a characteristic unit for S in this way, there is only one that simplifies the total number of parameters needed to define the system of equations. Note that though theoretically relevant, this choice is used to best simplify the model, not for theoretical clarity. From this atheoretical perspective, we are simply unitizing the second coefficient in Equation 1:

$$S_c = \frac{1}{kt_c} = \frac{l_R}{k}$$

Lastly, we assign a characteristic unit for work, W_c. This is done by setting the characteristic unit of work to be equal to the characteristic unit of the ready state, R_c weighted by the impact that uncoordinated effort has on work, β_U. This ensures that the work done is measured in perspective of the rate at which work is done in an uncoordinated manner. Again, while this has theoretical meaning, it is a choice of convenience to simplify the model. Atheoretically, we are simply unitizing the first coefficient in Equation 3:

$$W_c = R_c\beta_U = \frac{m}{l_R}\beta_U$$

As noted, for each of these selections of characteristic units, we have various options. The general behavior of the system is not dependent on the selection, and the selection could have been done purely atheoretically by selecting characteristic units that best reduce the total number of parameters needed to describe the system. By describing the theoretical relevance of each, I hope to clarify notionally the effect of nondimensionalization. But such a theoretical foundation for nondimensionalization is not necessary to provide a lens into the qualitative patterns exhibited by the system. The completed nondimensionalized system is as follows:

$$\frac{d\rho}{d\tau} = 1 - \rho\gamma - \rho \tag{24}$$

$$\frac{d\gamma}{d\tau} = \frac{k}{l_R^2}p + \frac{m}{l_R^2}k\rho\gamma - \frac{l_S}{l_R}\gamma \tag{25}$$

$$\frac{d\omega}{d\tau} = \rho + \frac{\beta_C}{\beta_U}\rho\gamma \tag{26}$$

Finally, we define four parameters to simplify the dimensionless representation of the systems of equations. Although these parameters at face value are quite complicated, they bear theoretical meaning (and unlike the characteristic units used to derive these, the theoretical meaning is important to the interpretation of the patterns the system follows). To recognize this meaning, it is helpful to recall that by setting $t_c = \frac{1}{l_R}$ we have determined that instability of the ready state, l_R, defines time in our dimensionless system. Notably, defining time interims of a decay rate is a common practice $\frac{1}{l_R}$ appears in many of the dimensionless parameters and is a reminder that the value and meaning of the parameter is tied to the time scale. As long as we hold l_R constant, this can be treated as a scaling value that does not impact the interpretation of the given parameter.

Next, we note that two of the parameters have a product between c and either m or p. The way in which we interpret these results depends on the variables of most interest to us. If we are interested in the impact of a motivational intervention, we would likely want to assume that k is held constant allowing for us to interpret $\frac{km}{l_R^2}$ as a weighted value for m. In most cases, I suggest that motivation, as presented in this model, is the least relevant of the three (i.e., m, p, and k) and for this reason, I explicitly define the parameters in a way that allows us to define a parameter for each of p and k as long as we assume m is held constant. This treats $\frac{m}{l_R^2}$ as simply a scaling factor. With these notes, we are prepared to theoretically define the parameters for the system.

First, there is a coupling strength parameter, $k^{\star}$. This is directly proportional to the original coupling strength, k, as well as the motivational input into the system, m. It also accounts for the ready state stability, l_R (used to represent time) loss parameter. Conceptually, this value represents the amount of coordinated effort performed over time as a function of *in situ* coordination. Perhaps more usefully, holding motivation, information loss, and the stability constant, $k^{\star}$ provide insight into the impact of coupling on the system:

$$k^{\star} = \frac{m}{l_R^2} k$$

Next there is a parameter, r_l, that describes the ratio of decay of the ready state compared to the decay of the signal. This fraction has the loss term for the signal on top, so the faster coordination information degrades (i.e., the less stable the signal is relative to the ready state), the larger this parameter's value will be. Similarly, small values for r_l imply strong stability of the signal compared to the stability of the ready state.

$$r_l = \frac{l_S}{l_R}$$

The third parameter represents the ratio of direct coordination information (i.e., p driven by *a priori* coordination) to the total motivational strength (i.e., m). This is represented as $p^{\star}$. Conceptually, this is a ratio between *a priori* and *in situ* coordination. The larger this ratio is, the more effectively the team coordinated *a priori*, relative to the total amount of motivation.

$$p^{\star} = \frac{p}{m}$$

Lasty, we define a parameter representing the coordination interdependence ratio, r_β. This is the effectivness of coordinated effort, β_C, compared to the effectiveness of uncoordinated effort, β_C. This could also account for inefficiencies in coordinated effort due to subjects such as process loss. In general, we would assume $r_\beta > 1$ because coordinated effort should be more effective than non-coordinated effort. However, it is possible for β_U to be larger than β_c in cases where there are high coordination costs and the work tasks are independent (this would lead to $r_\beta \leq 1$). In some extreme cases where coordination is absolutely essential, it is possible for β_u to actually be negative; however, for the present time we will assume $\beta_U > 0$, so $r_\beta > 0$.

$$r_\beta = \frac{\beta_C}{\beta_U}$$

We can substitute these values yielding the simplified, dimensionless system requiring only 4 parameters (along with the three state variables: ρ - dimensionless ready state, γ - dimensisonless coordination information, and ω - dimensionless work) to define:

$$\frac{d\rho}{d\tau} = 1 - \rho\gamma - \rho \tag{24a}$$

$$\frac{d\gamma}{d\tau} = k^\star p^\star + k^\star \rho\gamma - r_l\gamma \tag{25a}$$

$$\frac{d\omega}{d\tau} = \rho + r_\beta\rho\gamma \tag{26a}$$

APPENDIX C: SOURCE CODE

In this appendix I provide the source code used to run simulations found in this dissertation.

CASER Source Code:

The CASER model was analytically simulated using R.

```
######### R Code for CASER MODEL ##########

library(ggplot2)

N = 60

set.seed(42)


gamma = (1:N)/(2/3*N)

rho_rnc = 1/(1+gamma)

rho_gnc <- function(gamma, cstar=1, rp=1, rl =1){

 return(rl/cstar - rp/gamma)

}


dir1 = rho_gnc(gamma,1,.1,.5)

dir2 = rho_gnc(gamma,1,0.00001,.5)

dir3 = rho_gnc(gamma,1,.1,1)

dir4 = rho_gnc(gamma,1,0.00001,1)

dir5 = rho_gnc(gamma,1,.1,1.5)

dir6 = rho_gnc(gamma,1,0.00001,1.5)
```

```
# df = data.frame(gamma = rep(gamma,7), dgdt = c(rho_rnc,
dir1,dir2,dir3,dir4,dir5,dir6), group = rep(1:7, each = 1500), l =
c(rep(0,1500),rep(c(.5,1,1.5),each = (2*N))), rp = c(rep(0,1500),rep(rep(c(0,.1),each =
1500),3)))
df_gnc = data.frame(gamma = rep(gamma,6), rho = c(dir1,dir2,dir3,dir4,dir5,dir6), group
= rep(1:6, each = N), l = c(rep(c(1.5,1,.5),each = (2*N))), rp = c(rep(rep(c(0.01,.1),each =
N),3)))

df_rnc = data.frame(gamma = rep(gamma,6), rho = rho_rnc)
rho_gnc2 <- function(gamma, cstar=1, rp=1, rl =1){
  return(rep(rl/cstar, length(gamma)))
}
dir1 = rho_gnc2(gamma,1,.1,.5)
dir2 = rho_gnc2(gamma,1,0.01,.5)
dir3 = rho_gnc2(gamma,1,.1,1)
dir4 = rho_gnc2(gamma,1,0.01,1)
dir5 = rho_gnc2(gamma,1,.1,1.5)
dir6 = rho_gnc2(gamma,1,0.01,1.5)

# df = data.frame(gamma = rep(gamma,7), dgdt = c(rho_rnc,
dir1,dir2,dir3,dir4,dir5,dir6), group = rep(1:7, each = 1500), l =
```

```
c(rep(0,1500),rep(c(.5,1,1.5),each = (2*N))), rp = c(rep(0,1500),rep(rep(c(0,.1),each =
1500),3)))
df_gnc2 = data.frame(gamma = rep(gamma,6), rho = c(dir1,dir2,dir3,dir4,dir5,dir6),
group = rep(1:6, each = N), l = c(rep(c(1.5,1,.5),each = (2*N))), rp =
c(rep(rep(c(0.01,.1),each = N),3)))

ggplot() + ylim(0,1.6) + theme_apa() +
  geom_line(data = df_gnc, aes(x=gamma, y=rho, group = group, color = as.character(l),
linetype = as.character(rp)),size = 1.25)+
  geom_line(data = df_rnc, aes(x = gamma, y=rho),size=1.25)


gamma = (1:N)/(2/3*N)
rho = 1/(1+gamma)
dgdt <- function(gamma,rho, c, rp, l){
  return(c*rp+c*rho*gamma - l*gamma)
}
dir1 = dgdt(gamma,rho,1,.1,.5)
dir2 = dgdt(gamma,rho,1,0,.5)
dir3 = dgdt(gamma,rho,1,.1,1)
dir4 = dgdt(gamma,rho,1,0,1)
dir5 = dgdt(gamma,rho,1,.1,1.5)
```

```
dir6 = dgdt(gamma,rho,1,0,1.5)

df = data.frame(gamma = rep(gamma,6), dgdt = c(dir1,dir2,dir3,dir4,dir5,dir6), group =
rep(1:6, each = N), l = rep(c(1.5,1,.5),each = (2*N)), rp = rep(c(0,.1),each = N))

ggplot(data = df, aes(x=gamma, y=dgdt, group = group, color = as.character(l), linetype =
as.character(rp))) +
  geom_line(size=1.2) + ylim(-.25,.25) + geom_hline(yintercept=0)+ theme_apa()

f2 <- function(c, rp, l){
  h = c + c*rp - l
  return((h + sqrt(h^2 + 4*l*c*rp))/(2*l))
}
N=100
k = 4
df = data.frame(c = rep(1,N*k),rp = rep((1:k-1)/(2*(k-1)),each = N),l =
rep(1/((1:N)/(N/2)),k))
df$rcl = df$c/df$l
df$f2 = f2(1,df$rp, df$l)

ggplot(data = df, aes(x=rcl, y=f2, group = as.character(rp), color = rp)) +
  geom_hline(yintercept=0, linetype = "dashed",size = 1.2)+ geom_line(size = 1.2) +
theme_apa()
```

```
###########################################################################
```

Code for CSN Model

The CSN Model Code is more complicated and split into different code files for running the model itself as well as analysis/data visualization code. The model was run in python and the analysis and data visualization was run in R.

coordinationModel.py Source Code

```python
from utils import getTheta
from utils import vr_crc
from utils import getCircD
import numpy as np
from enum import Enum

from scipy.linalg import circulant
from scipy.special import erf


class R_Type(Enum):
    FLOOR = 0
    ROUND = 1
    CEILING = 2
    RANDOM = 3
    COMBINED = 4
    COMPLEX = 5
    DEFAULT = 0
```

```python
class statePlan():

    def __init__(self, P=None, change_times=[0], sig2_t=None, sig2_d=None, D2=None):

        self.trivial = True if (P is None or np.isinf(sig2_d)) else False

        self.S = 0 if P is None else P.shape[0]

        # P is S by T by A or  S by T

        # P active up until the corresponding change time, at that value switches

        self.sig2_t = sig2_t

        self.sig2_d = sig2_d

        self.D2 = D2

        self.change_times = change_times

        self.P = self.pUncertainty(P, sig2_d, D2)


    def pUncertainty(self, P, sig2_d=None, D2=None):

        if self.trivial: return None

        sig2_d = self.sig2_d if sig2_d is None else sig2_d

        if sig2_d == 0: return P

        D2 = self.D2 if D2 is None else D2

        if sig2_d is None or D2 is None: return P


        M = np.zeros(P.shape)

        D_star = np.exp(-D2 / (2 * sig2_d))


        if P.ndim == 2:

            for t in range(P.shape[-1]):

                M[:, t] = D_star @ P[:, t]

        else:

            for a in range(P.shape[2]):
```

```
            for t in range(P.shape[1]):
                M[:, t, a] = D_star @ P[:, t, a]

        return M

    def getP(self, t, agent=None, weights=None):
        if self.trivial: return None
        if weights is None: return self.getP_vec(t, agent).reshape((self.S, 1)) @
np.ones((1, self.S))

        M = np.empty((self.S, self.S))
        for j in range(self.S):
            M[:, j] = (self.getP_vec(t, agent, weights[j])).squeeze()
        return M

    def getP_vec(self, t, agent=None):
        P = self.P if (agent is None or self.P.ndim == 2) else self.P[:, :, agent]

        if self.sig2_t is None:
            index = None
            for i in range(len(self.change_times)):
                if self.change_times[i] > t:
                    index = i
                    break
            M = P[:, -1] if index is None else P[:, index] if index >= 0 else
np.ones(P.shape[0])
            # Gives the last P column if t >= ax change time
            # Gives ones if t before first change time
```

```
            # give the P column number one less than the first change_time that is
more than current time otherwise

        elif np.isinf(self.sig2_t):
            M = np.sum(P, 1)
        else:
            M = np.ones((P.shape[0])) * (1 + erf((self.change_times[0] - t) /
self.sig2_t)) / 2
            for i in range(len(self.change_times) - 1):
                pv = (P[:, i]).squeeze()
                M += pv * (1 + erf((t - self.change_times[i]) / self.sig2_t)) * (
                             1 + erf((self.change_times[i + 1] - t) / self.sig2_t)) /
4
            M += (P[:, -1]) * (1 + erf((t - self.change_times[-1]) / self.sig2_t)) /
2

        if M.sum() == 0: return np.ones(((P.shape[0])))

        return M



class systemTransitionFunction:
    def __init__(self, M, n_actors, n_states, common=None, fixedRotation=False,
rot_velocity=0, dt=1, type=None):
        M = np.asarray(M)
        if M.ndim == 3 and common: raise ValueError("Common but gave 3D M")
        if M.shape != (n_states, n_states) and M.shape != (n_states, n_states,
n_actors):
```

```
            raise ValueError("Invalid matrix shape.")
        self.OriginalM = M
        common = common if common is not None else M.ndim == 2
        self.isCommon = common
        self.n_actors = n_actors
        self.n_states = n_states
        self.fixedRotation = fixedRotation
        self.dt = dt
        self.rot_velocity = rot_velocity
        self.type = type if type is not None else R_Type.DEFAULT

        if self.fixedRotation:
            self.applyFixedRotation(rot_velocity, dt=dt)

    def getOmega(self, agent=None, rv=None, dt=None, type=None):
        # TODO fix handling dt. It currently treats it as if dt does nothings
        if dt is not None: raise ValueError("Can not handel changing dt at this
point")
        if rv is not None or dt is not None:
            rv = self.rot_velocity if rv is None else rv
            self.set_rotation_velocity(rv, dt)

        rv = self.rot_velocity
        dt = self.dt
        rad = rv * dt
        rad = rad if np.isscalar(rad) else rad[agent]

        if self.fixedRotation:
```

```
            return self.M_r if self.M_r.ndim == 2 else self.M_r[:, :, agent]

        else:
            M = self.OriginalM.copy() if self.isCommon else (self.OriginalM[:, :,
agent]).copy()
            return self.rotateMbyRad(M, rad, type)

    def set_rotation_velocity(self, rv, dt=None):
        dt = self.dt if dt is None else dt
        if self.fixedRotation:
            self.applyFixedRotation(rv, dt=dt)

        self.dt = dt
        self.rot_velocity = rv

    def applyFixedRotation(self, rv, type=None, dt=None):
        type = type if type is not None else self.type
        if dt is not None: dt = self.dt
        rad = rv * dt
        self.M_r = self.rotateMbyRad_n(self.OriginalM, rad, type)

    def rotateMbyRad_n(self, M, rad, type=None):
        type = type if type is not None else self.type
        if M.ndim == 2:
            if np.isscalar(rad):
                return self.rotateMbyRad(M, rad, type)  # CHECK: Should this bee
self.isCommon? Also may need copy here
            elif len(set(rad)) == 1:
```

```
                return self.rotateMbyRad(M, rad[0], type)
            else:
                M_full = np.empty(M.shape + rad.shape)
                for a in range(len(rad)):
                    M_full[:, :, a] = self.rotateMbyRad(M[:, :], rad[a], type)
                return M_full

        else:
            M_full = np.empty(M.shape)
            for a in range(M.shape[-1]):
                rad_actor = rad if np.isscalar(rad) else rad[a]
                M_full[:, :, a] = self.rotateMbyRad(M[:, :, a], rad_actor, type)
            return M_full

    def rotateMbyRad(self, M, rad, type=None):
        type = type if type is not None else self.type
        d_raw = (rad * self.n_states) / (2 * np.pi)
        d = int((rad * self.n_states) // (2 * np.pi))
        p = ((rad * self.n_states) % (2 * np.pi)) / (2 * np.pi)
        R_floor = np.roll(M.copy(), d, 0)
        if type == R_Type.FLOOR:
            return R_floor
        elif (type == R_Type.ROUND and p > .5) or type == R_Type.CEILING:
            R = np.roll(R_floor, 1, 0)
        elif type == R_Type.RANDOM:
            shift = np.random.choice([0, 1], size=(1), p=[1 - p, p])[0]
            R = np.roll(R_floor, shift, 0)
        elif type == R_Type.COMBINED:
```

```
            R = R_floor * (1 - p) + np.roll(R_floor, 1, 0) * p
        elif type == R_Type.COMPLEX:
            lam, Q = np.linalg.eig(np.roll(np.identity(M.shape[0]), 1, 0))
            R = Q @ np.diag(lam ** d_raw) @ np.linalg.inv(Q)
        else:
            raise ValueError("Invalid rotation type. Found: " + str(type))

        return R



## Currently Coordination model takes everything at initialization. I would like to
separate out
# different initialization methods
# also note that D and TaskDependence are distance matrices, likely generated from
spectral distances

class CoordinationModel:
    def __init__(self, n_actors, n_states,
                 k=1, m=None, w=None, w_dist=None, dt=1,
                 Omega=None, D=None, TaskDependence=None,
                 interdependenceWeights=None,
                 temporal_correction=False, rotational_correction=False,
                 x_0=None,
                 random_seed=None,
                 Plan=None,
                 p_change_times=[0],
                 rho_t=None,
                 rho_d=0,
```

```
             pD_index=None,
             deterministic=True,
             ):
    """

    :param integer n_actors: The number of actors in the system

    :param integer n_states: The number of stats that actors can occupy

    :param k: The coupling strength parameter(s). Default 1. Typically between 0
and 1. This controls how
    strongly actors are influenced by each other If a single value k is applied
to each actor. If a single
    dimensional array, (length = n_actors) this represents how attractive each
actor is. If a 2-dimensional
    array, k[i,j] indicates how strongly actor_i is influenced by actor_j. This
is not necessarily symmetric.
    :type k: float OR n_actors length ndarray OR n_actors X n_actors ndarray

    :param m: The mass parameter or propensity for actors to remain in the same
state. Default None. If a single
    value, the parameter is applied to all actors. If it is a n_actor ndarray
each element is the mass parameter
    for each given actor. If Omega is None this is used to calculate Omega.
Calculated as rotated Gaussian based
    on distance from the first matrix in D rotated by w.
    :type m: float OR n_actors length ndarray or None
```

:param *w: The natural frequency of actors. If a single value all actors are given the same frequency. If an*

array, give the natural frequency of each actor.

:type *w: n_actors length ndarray OR None*

:param *w_dist: Distribution of natural frequencies. The mean and variance of frequencies. If None,*

frequencies are set by w, or ignored. This overwrites values input by w.

:type *w_dist: (float, float) OR None*

:param *float dt: The discrete time interval. Default 1. This is always positive and typically less than or*

equal to 1.

:param *Omega: Transition matrix. Default identity matrix if None, and m is None. Must be positive valued matrix*

where columns add up to 1.

:type *Omega: n_statesXn_states array OR n_statesXn_statesXn_actors array*

:param *n_statesXn_states TaskDependence: Interdependence matrix. Matrix representing positive an negative effects of*

states on each other. D[i,j] represents the extent to which state_i is facilitated (if positive) or inhibited

(if negative) by someone being in state_j. D[i,j] = 0 indicates i is independent of j.

:param *boolean temporal_correction: Weather to apply a time based correction to Xi*

```
        :param boolean rotational_correction: Weather to apply a rotation based
correction to Xi accounting for the
        fact that interdependence does not act in the same direction as motion.
        :param x_0: initial states for each actor. If single value all actors start
at the same point. If 1D vector (n_actors)
        it provides position for each actor. If 2D array (n_statesXn_actors) it gives
probabilities for each actor being at each position.
         If None randomly actors are randomly assigned
        :type x_0: float OR ndarray OR None

        :param random_seed: Random Seed
        """
        if random_seed is not None: np.random.seed(random_seed)

        self.n_states = n_states
        self.n_actors = n_actors
        self.internalTime = 0

        if dt < 0:
            raise ValueError("dt must be positive: input dt is " + str(dt))
        else:
            self.dt = dt

        self.temporal_correction = temporal_correction
        self.rotational_correction = rotational_correction

        if np.isscalar(k):
```

```
            self.k = np.full((n_actors, n_actors), k / (n_actors - 1))

        else:
            k = np.asarray(k)
            if k.ndim == 1 and len(k) == n_actors:
                self.k = np.ones((n_actors, 1)) @ [k / (n_actors - 1)]
            elif k.ndim == 2 and k.shape == (n_actors, n_actors):
                self.k = k / (n_actors - 1)
            else:
                raise ValueError("Invalid k value --- k (coupling coefficient) must
be a scalar, a 1D or a 2D ndarray")

        np.fill_diagonal(self.k, 0)
        self.common_w = False
        if w is None and w_dist is None:
            self.common_w = True
            self.w = np.full((n_actors), 0)
        elif w_dist is not None:
            if len(w_dist) == 2:
                self.w = np.random.normal(w_dist[0], w_dist[1], n_actors)
            else:
                raise ValueError("Invalid w_dist value --- w_dist Must be (float,
float) or None.")

        else:
            if np.isscalar(w):
                self.common_w = True
                self.w = np.full((n_actors), w)
```

```
            elif len(w) == n_actors:
                self.w = np.asarray(w)
            else:
                raise ValueError("Invalid w value --- w must be n_actor length array,
scalar or None.")

        if TaskDependence is None and D is None:
            TaskDependence = getCircD(self.n_states) ** 2
            D = TaskDependence
        elif TaskDependence is None:
            TaskDependence = D
        elif D is None:
            D = getCircD(self.n_states) ** 2

        self.n_interdependence_d = 1 if TaskDependence.ndim == 2 else
TaskDependence.shape[-1]

        self.TaskDependence = np.asarray(TaskDependence)

        if interdependenceWeights is None:
            self.D_w = np.ones((self.n_interdependence_d))
        elif np.isscalar(interdependenceWeights):
            self.D_w = np.full(self.n_interdependence_d, interdependenceWeights)
        else:
            self.D_w = interdependenceWeights

        if m is None: m = 1
        if np.isscalar(m):
```

```
            self.sigma2_m = self.sig2FromM(m)
        else:
            self.sigma2_m = np.asarray([self.sig2FromM(x) for x in m])

        self.sharedOmega = False
        if Omega is not None:
            Omega = np.asarray(Omega)
            # self.Omega = Omega
            if Omega.ndim == 2:
                self.sharedOmega = True
                if Omega.shape != (n_states, n_states):
                    raise ValueError("Omega has invalid shape. Expected (" +
str(n_states) + ", " +
                                     str(n_states) + ") but got " + str(Omega.shape))
            elif Omega.ndim == 3 and Omega.shape != (n_states, n_states, n_actors):
                raise ValueError("Omega has invalid shape. Expected (" +
str(n_states) + ", " +
                                 str(n_states) + ", " + str(n_actors) + ") but got "
+ str(Omega.shape))



        else:
            # m = np.asarray(m)
            if np.isscalar(m):
                self.sharedOmega = True
                Omega = self.getOmegaFromD(self.dt * self.sigma2_m, D)
                # Omega = self.getOmegaFromD(self.dt * self.sigma2_m, D)
            else:
```

```
                m = np.asarray(m)
                if len(m) != n_actors: raise ValueError(
                    "Invalid m value. Expected None, scaler, or array of length " +
str(n_actors))
                Omega = np.empty((n_states, n_states, n_actors))
                for a in range(n_actors):
                    Omega[:, :, a] = self.getOmegaFromD(self.dt * self.sigma2_m[a],
D)
                    raise ValueError("There may be an Issue with tThis code")
                # TODO fix line 319 code... self.getOmegaFromD(self.sigma2_m[a], D,
w[a] * dt)

        self.Omega = systemTransitionFunction(Omega, n_actors=n_actors,
n_states=n_states,
                                              fixedRotation=not self.w.any(),
common=self.sharedOmega,
                                              rot_velocity=self.w, dt=dt,
type=R_Type.RANDOM)
        # M, n_actors, n_states, common = None, fixedRotation = False, rot_velocity =
0, rotated = False, dt = 1, type = None):

        X = np.zeros((self.n_states, self.n_actors))
        if x_0 is None:
            x_0_index = np.random.randint(self.n_states, size=self.n_actors)
            for j, i in enumerate(x_0_index):
                X[i, j] = 1
                # TODO do not like that this code is repeated...
        elif np.isscalar(x_0):
```

```
            X[x_0, :] = np.ones((n_actors))
        else:
            x_0 = np.asarray(x_0)
            if x_0.ndim == 1:
                if len(x_0) != (n_actors): raise ValueError(
                    "x_0 is wrong length. Expected n_actors (i.e., " + str(n_actors)
+ ") but got " + str(x_0.shape))
                for j, i in enumerate(x_0):
                    X[i, j] = 1
            elif x_0.ndim == 2:
                if x_0.shape != (n_states, n_actors): raise ValueError(
                    "x_0 is wrong shape. Expected n_actors (i.e., " + str(n_states) +
", " + str(
                        n_actors) + ") but got " + str(x_0.shape))
                X = x_0


            else:
                raise ValueError(
                    "initial condition (x_0), has too many dims. Expected scaler, 1D,
or 2D but got " + str(x_0.ndim))
        self.X = X


        pD = D if (pD_index is None or self.TaskDependence.ndim == 2) else
self.TaskDependence[:, :, pD_index]


        self.plan = statePlan(P=Plan, change_times=p_change_times, sig2_t=rho_t ** 2,
                              sig2_d=(rho_d ** 2) * self.sigma2_m, D2=pD)
```

```
        self.deterministic = deterministic

    def step(self, deterministic=None, dt=None, rotational_correction=None,
time_correction=None):
        # TODO fix handling dt. It currently treats it as if dt does nothings
        if dt is not None: raise ValueError("Can not handel changing dt at this
point")
        if dt is None: dt = self.dt
        if deterministic is None:
            deterministic = self.deterministic
        else:
            self.dt = dt
        if rotational_correction is None: rotational_correction =
self.rotational_correction
        if time_correction is None: time_correction = self.temporal_correction
        X_next = np.empty((self.n_states, self.n_actors))

        for a in range(self.n_actors):
            x_past = self.X[:, a]
            sigma2_m = self.sigma2_m if np.isscalar(self.sigma2_m) else
self.sigma2_m[a]
            Omega = self.Omega.getOmega(a, type=R_Type.RANDOM)
            Xi = np.ones((self.n_states, self.n_states))
            P = self.plan.getP(self.internalTime, a)
            # t = self.internalTime
            hi = True
            for alter in range(self.n_actors):
                if a == alter: continue
```

```
                k = self.k if np.isscalar(self.k) else self.k[a] if self.k.ndim == 1
else self.k[a, alter]
                alter_loc_prob = self.X[:, alter]
                for depend in range(self.n_interdependence_d):
                    w = self.D_w if np.isscalar(self.D_w) else self.D_w[depend]
                    TD = self.TaskDependence if self.n_interdependence_d == 1 else
self.TaskDependence[:, :, depend]
                    TD = TD * w
                    Xi *= self.calculateXi_2(alter_loc_prob, TD, sigma2_m,
coupling=k,

rotational_correction=rotational_correction,
                                             time_correction=time_correction)

            transition = (Xi * Omega) if P is None else (P * Xi * Omega)
            x = transition @ x_past
            # print("Expected Var: " + str(1/(1/(dt * sigma2_m)+ 1/(sigma2_m/k))) +".
Found Var: " + str(np.var(x)))
            # print()
            if np.isclose(np.sum(x), 0): x = np.ones(self.n_states)
            x = x / np.sum(x)

            if deterministic:
                flip = np.random.random()
                x_d = np.zeros(self.n_states)
                i = 0
                found = False
                while not found:
```

```
                if found:
                    continue
                elif i >= len(x):
                    hi = True
                elif flip <= x[i]:
                    x_d[i] = 1
                    found = True
                else:
                    flip -= x[i]
                    i += 1

            x = x_d
        X_next[:, a] = x
    self.X = X_next
    self.internalTime += dt
    return (X_next)

def sig2FromM(self, m):
    return 1 / m

def getOmegaFromD(self, sig2, D2, isCirculant=False):
    """

    :param sig2: Variance value
    :param D2: Squared distance metric
    :param theta: The angle changed. typically w * dt
    :param isCirculant: If circulant there is a short cut to computations
    :return: Omega matrix
```

```
        """
        if isCirculant:
            v = np.exp(-D2[0, :] / 2 * sig2)
            Omg_star = circulant(v)
        else:
            Omg_star = np.exp(-D2 / (2 * sig2))
        return Omg_star

    def calculateXi_2(self, alter_loc_prob, D2, sigma2_m, coupling=None,
rotational_correction=False,
                      time_correction=False, S=None):
        if S is None:
            S = self.n_states

        Xi_sum = np.zeros((S, S))
        for a in range(S):
            if alter_loc_prob[a] > 0:
                Xi_sum += alter_loc_prob[a] * self.calculateXi(a, D2[a, :], sigma2_m,
coupling, rotational_correction,
                                                               time_correction, S)
        return Xi_sum

    def calculateXi(self, alter_loc, D2_alter, sigma2_m, coupling,
rotational_correction=False, time_correction=False,
                    S=None):

        if S is None:
            S = self.n_states
```

```
        if coupling == 0: return np.ones((S, S))

        h = self.dt if time_correction else 0
        rc = np.ones((S))
        if rotational_correction:
            # TO
            theta_d = 2 * np.pi * np.roll(np.arange(S) - (S - 1) // 2, -((S - 1) //
2) + alter_loc) / S
            sinTD = np.sin(theta_d)
            zero_sin = np.isclose(sinTD, 0)
            zero_theta = np.isclose(theta_d, 0)
            zero_index = np.logical_and(zero_sin, zero_theta)
            infty_index = np.logical_and(zero_sin, np.logical_not(zero_theta))

            sinTD[zero_sin] = 1
            rc = theta_d / sinTD
            rc[zero_index] = 1
            rc[infty_index] = np.infty

        D2 = np.repeat(np.asarray(D2_alter)[np.newaxis].T, S, 1)  # distance from
potential positions to alter position
        sigma2_xi = sigma2_m * (rc / coupling - h)  # sigma based on ego's current
position and alter's position
        # if sigma2_xi > np.var(D2_alter):
        #     return np.ones((S, S))
        Sig2 = np.repeat(sigma2_xi[np.newaxis], S, 0)
        Xi = np.exp(- D2 / (2 * Sig2))
```

```
        return Xi

    def getState(self):
        return np.sum(self.X, 1)
```

batchRunner.py Source Code

```
import time
import networkx as nx
import pandas as pd
import numpy as np

from coordinationModel import CoordinationModel
from utils import cmParamSet, getSpectralDistance, getCircD, InverseDAdj, Lps,
rayleighQ, eigenScaled, getTheta, \
    spectralEmbedding
from mesa.batchrunner import ParameterProduct


class batchRunner():
    def __init__(self, fixed_Params, variable_Params=None, iterations=1, steps=1):
        self.iterations = iterations
        self.steps = steps
        self.fixed_Params = fixed_Params
        self.variable_Params = variable_Params

    def run(self, fixed_x0=True):
        varableParamProd = ParameterProduct(self.variable_Params) if
```

```
self.variable_Params is not None else [
            {"Fixed": True}]

        data = pd.DataFrame(
            columns=["id", "iteration", "step", 'Lps_Coordination',
'Adjacency_Coordination', 'theta', 'r', 'DLC',
                     'DAC'].extend(list(self.variable_Params.values())))
        id = 0

        x_0_index = np.random.randint(self.fixed_Params['n_states'],
                                      size=self.fixed_Params['n_actors']) if fixed_x0
else None

        for vps in varableParamProd:
            p = cmParamSet({**self.fixed_Params, **vps})
            p.x_0 = x_0_index
            if p.D is None: p.D = getCircD(p.n_states) ** 2
            DAdj = InverseDAdj(np.sqrt(p.D))
            DL = Lps(DAdj)

            if hasattr(p, "AdjM"):
                if p.AdjM is None:
                    p.AdjM = DAdj
                if not hasattr(p, "TDD"):
                    dims = p.AdjM_dims if hasattr(p, "AdjM_dims") else 2
                    p.TDD = getSpectralDistance(p.AdjM, dims)
            else:
                p.AdjM = DAdj
```

```
            L = Lps(p.AdjM)
            p.AdjM = eigenScaled(p.AdjM)

            if hasattr(p, 'p'):
                if hasattr(p, 'rho_t'): p.rho_t = p.rho_t / p.p if p.p != 0 else
np.inf
                if hasattr(p, 'rho_d'): p.rho_d = p.rho_d / p.p if p.p != 0 else
np.inf

            for r in range(self.iterations):
                mod = CoordinationModel(n_actors=p.n_actors, n_states=p.n_states,
k=p.k, m=p.m, w=p.w, w_dist=p.w_dist,
                                        dt=p.dt, Omega=p.Omega, D=p.D,
TaskDependence=p.TDD,

interdependenceWeights=p.interdependenceWeights,
                                        temporal_correction=p.temporal_correction,
random_seed=p.random_seed,

rotational_correction=p.rotational_correction, x_0=p.x_0, Plan=p.Plan,
                                        p_change_times=p.p_change_times,
rho_t=p.rho_t, rho_d=p.rho_d,
                                        pD_index=p.pD_index,
deterministic=p.deterministic)

                state = mod.getState()
```

```
Lps_Coordination_vec = np.empty(self.steps + 1)
Adjacency_Coordination_vec = np.empty(self.steps + 1)
theta_vec = np.empty(self.steps + 1)
r_vec = np.empty(self.steps + 1)
DLC = np.empty(self.steps + 1)
DAC = np.empty(self.steps + 1)


Lps_Coordination_vec[0] = rayleighQ(state - np.mean(state), L)
Adjacency_Coordination_vec[0] = rayleighQ(state, p.AdjM)
theta_vec[0], r_vec[0] = getTheta(state)
DLC[0] = rayleighQ(state - np.mean(state), DL)
DAC[0] = rayleighQ(state, DAdj)
for t in range(1, self.steps + 1):
    mod.step()
    state = mod.getState()
    Lps_Coordination_vec[t] = rayleighQ(state - np.mean(state), L)
    Adjacency_Coordination_vec[t] = rayleighQ(state, p.AdjM)
    theta_vec[t], r_vec[t] = getTheta(state)
    DLC[t] = rayleighQ(state - np.mean(state), DL)
    DAC[t] = rayleighQ(state, DAdj)
iterRows = {**{"id": str(id), "iteration": r, "step":
np.arange(self.steps + 1),
                'Lps_Coordination': Lps_Coordination_vec,
                'Adjacency_Coordination': Adjacency_Coordination_vec,
'theta': theta_vec, 'r': r_vec,
                'DLC': DLC, 'DAC': DAC}, **vps}
if 'p_change_times' in iterRows: iterRows['p_change_times'] =
len(p.p_change_times)
```

```
                df = pd.DataFrame(iterRows)

                data = data.append(df)

                id += 1


        return (data)




class batchRunner2X2(batchRunner):

    def run(self, hp_gap, verbose=True):

        varableParamProd = ParameterProduct(self.variable_Params) if
self.variable_Params is not None else [

            {"Fixed": True}]


        data = pd.DataFrame(

            columns=["id", "iteration", "step", 'Lps_Coordination',
'Adjacency_Coordination', 'theta', 'r', 'DLC',

                     'DAC',
'complexity'].extend(list(self.variable_Params.values())))

        id = 0


        if verbose:

            TotalSimCount = self.iterations * 2

            for key in self.variable_Params:

                TotalSimCount = TotalSimCount * len(self.variable_Params[key])

            StartTime = time.time()


        for vps in varableParamProd:

            p = cmParamSet({**self.fixed_Params, **vps})
```

```
        p.x_0 = None

        p.D = getCircD(p.n_states) ** 2
        DAdj = InverseDAdj(np.sqrt(p.D))
        DL = Lps(DAdj)

        for lh in range(2):
            if lh == 0:
                AdjM = DAdj
                TDD = p.D
                D_w = None
            else:
                dens = p.dens if hasattr(p, 'dens') else .25
                TDD = np.empty((p.n_states, p.n_states, 2))
                G = nx.gnm_random_graph(p.n_states, dens * (p.n_states *
(p.n_states - 1) / 2))
                AdjM = nx.to_numpy_array(G)
                AdjM = AdjM + .01  # ensure it is connected
                np.fill_diagonal(AdjM, 0)
                TDD[:, :, 0] = getSpectralDistance(AdjM, 2)
                TDD[:, :, 1] = 1 - 2 * np.identity(p.n_states)
                D_w = [1, -1]

            p.AdjM = AdjM
            p.TDD = TDD
            p.D_w = D_w

            L = Lps(p.AdjM)
```

```
                p.AdjM = eigenScaled(p.AdjM)

                ###### update plan based on graph
                v = spectralEmbedding(AdjM, 1)
                ordInd = np.argsort(v.squeeze())

                tg = self.steps // hp_gap
                evn = np.linspace(0, tg + tg % 2 - 2, self.steps // (hp_gap * 2) + tg % 2).astype(int)
                odd = np.linspace(1, tg - tg % 2 - 1, self.steps // (hp_gap * 2)).astype(int)

                P = np.zeros((p.n_states, tg, p.n_actors))
                for a in range(p.n_actors):
                    for i in range(len(evn)):
                        P[np.random.choice(ordInd[:p.n_actors]), evn[i], a] = 1
                    for i in range(len(odd)):
                        P[np.random.choice(ordInd[-p.n_actors:]), odd[i], a] = 1

                # P[:, a] = positive
                # P[:, b] = 1 - positive
                p.Plan = P
                if hasattr(p, 'p'):
                    if hasattr(p, 'rho_t'): p.rho_t = p.rho_t / p.p if p.p != 0 else np.inf
                    if hasattr(p, 'rho_d'): p.rho_d = p.rho_d / p.p if p.p != 0 else np.inf
```

```
                for r in range(self.iterations):
                    mod = CoordinationModel(n_actors=p.n_actors, n_states=p.n_states,
k=p.k, m=p.m, w=p.w,
                                            w_dist=p.w_dist,
                                            dt=p.dt, Omega=p.Omega, D=p.D,
TaskDependence=p.TDD,

interdependenceWeights=p.interdependenceWeights,

temporal_correction=p.temporal_correction, random_seed=p.random_seed,

rotational_correction=p.rotational_correction, x_0=p.x_0, Plan=p.Plan,
                                            p_change_times=p.p_change_times,
rho_t=p.rho_t, rho_d=p.rho_d,
                                            pD_index=p.pD_index,
deterministic=p.deterministic)

                    state = mod.getState()

                    Lps_Coordination_vec = np.empty(self.steps + 1)
                    Adjacency_Coordination_vec = np.empty(self.steps + 1)
                    theta_vec = np.empty(self.steps + 1)
                    r_vec = np.empty(self.steps + 1)
                    DLC = np.empty(self.steps + 1)
                    DAC = np.empty(self.steps + 1)

                    Lps_Coordination_vec[0] = rayleighQ(state - np.mean(state), L)
                    Adjacency_Coordination_vec[0] = rayleighQ(state, p.AdjM)
```

```
                    theta_vec[0], r_vec[0] = getTheta(state)
                    DLC[0] = rayleighQ(state - np.mean(state), DL)
                    DAC[0] = rayleighQ(state, DAdj)
                    for t in range(1, self.steps + 1):
                        mod.step()
                        state = mod.getState()
                        Lps_Coordination_vec[t] = rayleighQ(state - np.mean(state),
L)
                        Adjacency_Coordination_vec[t] = rayleighQ(state, p.AdjM)
                        theta_vec[t], r_vec[t] = getTheta(state)
                        DLC[t] = rayleighQ(state - np.mean(state), DL)
                        DAC[t] = rayleighQ(state, DAdj)
                    iterRows = {**{"id": str(id), "iteration": r, "step":
np.arange(self.steps + 1),
                                   'Lps_Coordination': Lps_Coordination_vec,
                                   'Adjacency_Coordination':
Adjacency_Coordination_vec, 'theta': theta_vec, 'r': r_vec,
                                   'DLC': DLC, 'DAC': DAC, 'complexity': lh}, **vps}
                    if 'p_change_times' in iterRows: iterRows['p_change_times'] = 1
if len(p.p_change_times) > 2 else 0
                    df = pd.DataFrame(iterRows)
                    data = data.append(df)
                    id += 1

                    Now = time.time()
                    if verbose:
                        TE = round(Now - StartTime, 1)
                        ETA = round((TE / id) * (TotalSimCount - id), 1)
```

```
                        print("\rSimulation " + str(id) + " of " + str(TotalSimCount)
+ ". Time Elappsed: " + str(
                            TE) + " seconds. Estmated time (seconds) remaining: " +
str(ETA * 2), end='')

        return data
```

utils.py Source Code

```
import numpy as np
from scipy.linalg import circulant
from scipy.spatial import distance_matrix


def getCircD(n):
    return circulant(getAngles(n))


def getAngles(S, x_0=0, ctr=0):
    x = np.linspace(x_0, x_0 + 2 * np.pi * (S - 1) / S, S)
    for i in range(S):
        if x[i] <= ctr - np.pi: x[i] = (x[i] + 2 * np.pi)
        if x[i] > ctr + np.pi: x[i] = (x[i] - 2 * np.pi)
    return x


def vr_crc(p):
    m = getTheta(p)
```

```
    x = getAngles(len(p), 0, m)

    return (vr(p, x, m))


def mn(p, x):
    n = len(x)
    sm = 0
    for i in range(n):
        sm += p[i] * x[i]
    return sm / sum(p)


def vr(p, x, m=None):
    n = len(x)
    if m is None: m = mn(p, x)
    ss = 0
    for i in range(n):
        ss += p[i] * (m - x[i]) ** 2
    return ss / sum(p)


def getTheta(x, normR=True):
    x = np.asarray(x)
    n = x.shape[0]
    v = np.exp(np.asarray(range(n)) * 2j * np.pi / n)
    vx = v @ x
    r = np.abs(vx) / sum(x) if normR else np.abs(vx)
```

```
    theta = np.angle(vx)

    if x.ndim > 1:

        for i in range(x.shape[1]):

            if np.isclose(np.abs(vx[i]), 0):

                theta[i] = np.nan

            elif theta[i] < 0:

                theta[i] += 2 * np.pi

    else:

        if np.isclose(np.abs(vx), 0):

            theta = np.nan

        elif theta < 0:

            theta += 2 * np.pi


    return theta, r



class BaseParamSet(object):

    def __init__(self, iterable=()):

        self.__dict__.update(iterable)



class cmParamSet(BaseParamSet):

    def __init__(self, params=()):

        default = {'n_actors': 6, 'n_states': 10, 'k': 1, 'm': None, 'w': None,
'w_dist': None, 'dt': 1, 'Omega': None,

                   'D': None, 'TaskDependence': None, 'interdependenceWeights': None,
'temporal_correction': False,

                   'rotational_correction': False,
```

```
                    'x_0': None, 'random_seed': None, 'Plan': None, 'p_change_times':
[0], 'rho_t': None, 'rho_d': 0,
                    'pD_index': None, 'deterministic': True}
        default.update(params)
        super().__init__(default)


def getSpectralDistance(M, dims=None, norm=2):
    v = spectralEmbedding(M, dims)
    return distance_matrix(v, v, norm)


def spectralEmbedding(M, dims=None, dropZero=False, lamWeight=False):
    L = Lps(M)
    lmda, v = np.linalg.eigh(L)
    idx = np.logical_not(np.isclose(lmda, 0)) if dropZero else np.arange(1, len(lmda)
- 1)
    lmda = lmda[idx]
    v = v[:, idx]
    if dims is None: dims = len(lmda)
    if lamWeight: v = v @ np.diag(1 / (lmda ** (1 / 2)))

    if dims < len(lmda):
        v = v[:, np.arange(0, dims)]

    return v
```

```python
def Lps(M, normalized=True):
    D = np.diag(np.sum(M, 0))
    L = D - M
    DISR = np.diag(1 / np.sqrt(np.sum(M, 0)))
    if normalized: L = DISR @ L @ DISR
    return L


def rayleighQ(x, A):
    return (x.T.dot(A).dot(x) / x.T.dot(x))


def getCordD(n):
    v = np.empty((n))

    for i in range(n):
        v[i] = (2 * np.sin(i * np.pi / (n))) ** 2

    return circulant(v)


def InverseDAdj(D):
    M = D.copy()
    np.fill_diagonal(M, 1)
    M = 1 / M
    np.fill_diagonal(M, 0)
    return M
```

```python
def eigenScaled(M):
    lmda, v = np.linalg.eigh(M)
    return M / np.abs(np.max(lmda))


def convergeRate(eps, cvp=.1):
    """
    estimate rate of convergence q from sequence esp
    """
    N = int(cvp * len(eps))
    if N <= 1: N = 3
    equl = np.mean(eps[-N:])
    eps = np.asarray(eps)
    eps = np.abs(eps - equl)
    eps += np.random.random(len(eps)) * .0001
    x = np.arange(len(eps) - 1)
    y = np.log(np.abs(np.diff(np.log(eps))))
    line = np.polyfit(x, y, 1)  # fit degree 1 polynomial
    q = np.exp(line[0])  # find q
    return q
```

simRuns.py Source Code

```python
from batchRunner import batchRunner2X2
import numpy as np


n = 6
```

```
S = 20

dens = .25

T = 100

hp_gap = 3

P_t_HighP = np.linspace(hp_gap, T - T % hp_gap, T // hp_gap)

P_t_LowP = [T // 2]

P_t = [P_t_LowP, P_t_HighP]


a = batchRunner2X2({'n_actors': n, 'dt': 1, 'n_states': S, 'm': 10, 'rho_t': T / 8,
'rho_d': 1, 'dens': dens},
                   {"k": np.linspace(0, 3, 16), 'p': np.linspace(0, 10, 5),
'p_change_times': P_t}, iterations=50,
                   steps=T)

data = a.run(hp_gap)

data.to_csv('sims.csv')
```

Analysis and Data Visualization Source Code

```
#########################################################

######### Analysis and data visualization conducted using R

library(tidyverse)

library(ggplot2)

library(stats)

library(viridis)

library(hrbrthemes)
```

```
df = read_csv("sims.csv")
names(df)[length(names(df))]<-"dynamics"

df1 = df %>% group_by(id,k,p,complexity,dynamics) %>% summarise(coord = -
mean(Lps_Coordination))
dfs = df1
dfs$coord = scale(dfs$coord)
dfs = dfs %>% mutate(k_sqrd = k*k, p_sqrd = p*p)
df1 = df1 %>% mutate(k_sqrd = k*k, p_sqrd = p*p)

fit_1 = lm(coord ~ k + p + k*dynamics + k * complexity + p*dynamics + p * complexity,
dfs)
summary(fit_1)

fit_all = lm(coord ~ k + p + k_sqrd + k*dynamics + k * complexity + p*dynamics + p *
complexity + k_sqrd*dynamics + k_sqrd * complexity, dfs)
summary(fit_all)

fit_all2 = lm(coord ~ k + p + k_sqrd + k*dynamics + k * complexity + p*dynamics + p *
complexity + k_sqrd*dynamics + k_sqrd * complexity + p_sqrd * dynamics +
p_sqrd*complexity, dfs)
summary(fit_all2)
```

```
fit5 = lm(scale(coord) ~ (k) + (p) + (k_sqrd) + (p_sqrd), dfs %>% filter(complexity == 0,
dynamics == 0))
fit6 = lm(scale(coord) ~ (k) + (p) + (k_sqrd) + (p_sqrd), dfs %>% filter(complexity == 1,
dynamics == 0))
fit7 = lm(scale(coord) ~ (k) + (p) + (k_sqrd) + (p_sqrd), dfs %>% filter(complexity == 0,
dynamics == 1))
fit8 = lm(scale(coord) ~ (k) + (p) + (k_sqrd) + (p_sqrd), dfs %>% filter(complexity == 1,
dynamics == 1))
round(summary(fit5)$coefficients,3)
round(summary(fit6)$coefficients,3)
round(summary(fit7)$coefficients,3)
round(summary(fit8)$coefficients,3)

df3= df1
df3['coord'] = scale(df3['coord'])
df3$p = as.factor(df3$p)
```

```
ggplot(df3 %>% filter(complexity == 0, dynamics == 0 ), aes(x = k, y = coord, group = p,
color = p, fill = p)) + geom_smooth(level = .95) + scale_color_viridis(discrete=T)+
scale_fill_viridis(discrete=T) + theme_ipsum()
ggplot(df3 %>% filter(complexity == 1, dynamics == 0 ), aes(x = k, y = coord, group = p,
color = p, fill = p)) + geom_smooth(level = .95) + scale_color_viridis(discrete=T)+
scale_fill_viridis(discrete=T) + theme_ipsum()
ggplot(df3 %>% filter(complexity == 0, dynamics == 1 ), aes(x = k, y = coord, group = p,
color = p, fill = p)) + geom_smooth(level = .95) + scale_color_viridis(discrete=T)+
scale_fill_viridis(discrete=T) + theme_ipsum()
ggplot(df3 %>% filter(complexity == 1, dynamics == 1 ), aes(x = k, y = coord, group = p,
color = p, fill = p)) + geom_smooth(level = .95) + scale_color_viridis(discrete=T)+
scale_fill_viridis(discrete=T) + theme_ipsum()
#####################################################
```