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COLLECTIVE SYNCHRONY IN TEAM SPORTS

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COLLECTIVE SYNCHRONY IN TEAM SPORTS

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ABSTRACT

Collective synchrony is the simultaneous occurrence of behavior, cognition, emotion, and/or physiology within a group of three or more people. In this dissertation, I draw from various literatures to inform exploratory empirical and methodological investigation of collective synchrony in team sports. These include physiological synchrony, which has been examined primarily in dyads, and collective behavior in sports teams.

In Manuscript 1, I present a conceptual framework of collective synchrony in team sports. I argue that three possible antecedents (copresence, shared task, and coordination) underlie the interindividual matching of emotion, behavior, and cognition. This matching contributes to collective behavioral synchrony and/or collective physiological synchrony. These are conceptualized as a coupled system due to the relationship between human movement and physiology. Collective flow, a collective psychological state that may include interindividual matching of emotion, behavior, and/or cognition, is included in the framework as a possible outcome of collective synchrony.

In Manuscript 2, I provide a systematic review of 29 studies of collective synchrony. In this review, I decided to include not only studies on team sports, but also studies of collectives encompassing a variety of settings, substantive aims, variables of interest, and analytical methods. My review focuses on several characteristics of this multidisciplinary pool of articles including the (a) contexts, populations, and synchrony variables examined; (b) analytical methods used; and (c) notable findings reported.

In Manuscript 3, I articulate and apply a regime-switching dynamic factor analytical approach to examine collective synchrony in collegiate men's and women's soccer teams. In Study 1, I analyze collective synchrony in two variables

characterizing women's soccer players' movements during competitive games. In Study 2, I investigate collective synchrony in men's soccer teammates' changes in heart rate during small-sided practice games. Reporting on the results of these studies, I show how features of substantive interest, such as the magnitude and prevalence of collective synchrony, can be parameterized, interpreted, and aggregated. I highlight several key findings of these studies as well as opportunities for future research, in terms of methodological and substantive aims for advancing the study of collective synchrony. Results from an applied simulation, through which I tested the analytical approach on data with characteristics similar to that analyzed in Studies 1 and 2, supplementary tables and figures, and R software code are provided in the appendices.

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MANUSCRIPT 1

A Conceptual Framework of Collective Synchrony in Team Sports

Abstract: In this paper, a conceptual framework of collective synchrony in team sports is introduced. Collective synchrony is the simultaneous occurrence of behavior, cognition, emotion, and/or physiology within a group of three or more people. It is argued that three possible antecedents (copresence, shared task, and coordination) underlie the interindividual matching of emotion, behavior, and cognition. This matching contributes to collective behavioral synchrony and/or collective physiological synchrony, which, as a consequence of the relationship between human movement and physiology, are a coupled system. Additionally, collective flow, which is a collective psychological state that may include interindividual matching of emotion, behavior, and cognition, is included in the framework as a possible outcome of collective synchrony.

1.1 Introduction

During competition, a sports team may collectively experience moments of failure or success, anxiety or exhilaration, threat or challenge, pressure or relative comfort. In televised team sports, commentators often draw conclusions, from visual cues such as players' body language, about the psyche of an entire team. For example, they make observations such as, "They really seem to be feeling the pressure now". Comments such as this one reflect assumptions about the contagion of psychological states such as anxiety, not only among teammates, but also, for example, emanating from the crowd in the stadium to the team itself. The motivation for this paper is to support the scientific study of a highly related question: Do teammates exhibit similar behavioral and psychological states in response to their common experiences during team performance?

When people participate together in shared activities (e.g., sports, performing arts, social interactions), they may exhibit some of the same behavioral, cognitive, emotional, and physiological outcomes. The presence of such associations or

interdependencies between multiple individuals has been referred to as *synchrony* [1, 2]. Synchrony in various movement attributes has been of interest to researchers in the human movement sciences (physical education, sport science, etc.), such as those seeking to quantify *collective behavior* in teams [3, 4, 5, 6, 7]. Social and physiological psychologists have extensively investigated *physiological synchrony* during social interactions, in particular with dyads [8].

Examining physiological synchrony in sports teammates may enable some inferences to be made about their cognition and emotion, but attempts to do so are certain to be confounded by the metabolic demands of physical exertion. Therefore, what is needed is a conceptual framework that accounts for relationships among teammates' physical movement (i.e., behavior), cognition, emotion, and physiology. In this paper, I propose a conceptual framework of *collective synchrony* in team sports, where "collective" refers to a group of three or more persons. In pursuit of such a framework, I incorporate ideas spanning multiple disciplines such as psychology, kinesiology, and business. In so doing, I aim for this framework to be a platform from which to pursue more comprehensive examination of collective synchrony, that is, encompassing behavioral, cognitive, emotional, and physiological signals. To introduce this framework, I include literature from domains beyond team sports in which groups of people typically engage in shared activities. Primarily these include contexts in which the shared activity is goal-directed (i.e., a *shared task*) such as performing arts, workplace, military, and academic settings. I also integrate some literature on shared activities that are not goal-directed such as social interactions among family members.

As I elucidate in greater detail below, central to my conceptual framework are two broad types of observable collective synchrony: collective behavioral synchrony and collective physiological synchrony. Although these types are often

considered separately (i.e., in different disciplines), by unifying them as a coupled system within this framework, I aim to accommodate possible explanations for why collective synchrony would occur in team sports. It is sometimes clear what kinds of indicators can reflect collective behavioral synchrony, such as in the deliberately practiced voluntary movements of rowing and synchronized swimming. However, it is not well understood what causes collective synchrony in the physiological systems of two or more individuals. People have very limited capacity to control, for example, their cardiovascular systems, and interindividually they are not coupled in any direct way [9]. Three possible antecedents have been enumerated based on existing literature on heart rate synchrony [9]. First, *copresence*, simply being together in a setting, may bring about behavioral and emotional contagion such as common facial expressions and affective states, leading to common physiological arousal. Second, physiological synchrony may be driven by the characteristics of a *shared task*, such as whether group members are constrained to be physically active, cognitively focused, breathing regularly, etc. in similar ways. Third, physiological synchrony may emanate from deliberate online *coordination* on the task, that is, arranging individual behaviors in pursuit of group goals [10]. In sum, the notions of copresence, shared task, and coordination, which were posited in previous literature [9], are incorporated in the current framework as antecedents of collective synchrony.

In addition to these antecedents, in the proposed framework I consider *collective flow* as a possible outcome of collective behavioral and physiological synchrony. Collective flow has been investigated in studies of organizations, most commonly in business but with some limited coverage in sport psychology [11, 12, 13]. This reflects the extension of Mihály Csíkszentmihályi's notion of psychological flow [14], often treated as an individual construct, to collectives.

My decision to incorporate collective flow is predicated on the idea that it may emanate from synchrony in cognition and emotion, which at present are challenging to measure directly and/or intensively during most performance settings including team sports. By contrast, technologies such as wearable sensors and Global Positioning System (GPS) tracking enable the intensive measurement of athletes' behaviors and physiology during training and competition.

In the next sections, I elaborate on the above mentioned elements of the conceptual framework of collective synchrony. This includes the antecedents copresence, shared task, and coordination (Section 1.2), the coupled system of collective behavioral and physiological synchrony (Section 1.3), and collective flow as a possible outcome (Section 1.4). Before proceeding, I issue the caveat that the terminology "collective synchrony" has been used elsewhere, in studies of synchrony among soccer teammates' movements [5, 15], in studies with deliberate synchronization of movements during a rhythmic task [16, 17], and in studies of synchrony of brain rhythms [18] and other types of coupled oscillators in physics [19]. However, the current paper is the first to present a conceptual framework of collective synchrony that incorporates behavior, cognition, emotion, and physiology by merging ideas from multiple disciplines.

1.2 Antecedents of Collective Synchrony

There is a hierarchy inherent in the aforementioned antecedents of collective synchrony. That is, in general the copresence of a group of people is prerequisite to their engagement in a shared task, which in turn is prerequisite to their coordination on the task. However, copresence may occur without the others. For example, a group of friends socializing would be copresent without engaging in, or deliberately coordinating on, a shared task. Likewise, a work group may engage in a shared task without deliberate online coordination. However, in

sports competition, a team is likely to demonstrate all three antecedents. That is, teammates are copresent in the arena, engaged in a shared task (i.e., competing against an opponent), and coordinating their individual efforts for the benefit of the team. In this section, I explain how each of these antecedents may contribute to interindividual matching of emotion, behavior, and cognition.

1.2.1 Copresence

Copresence, or simply being in the same place together, may account for some degree of interindividual matching of emotional and behavioral states, contributing, respectively, to physiological and behavioral synchrony. Among the variables that are often associated with physiological synchrony, experiencing a common psychosocial context (e.g., one that is embarrassing, frightening, jubilant, tense, etc.) is one way that copresence may give rise to physiological synchrony [8]. Additionally, copresence may engender *emotional contagion*, defined as "the tendency to automatically mimic and synchronize expressions, vocalizations, postures, and movements with those of another person and, consequently, to converge emotionally" [20]. Hatfield, Cacioppo, and Rapson [20] have presented evidence in support of the following three propositions. First, people subconsciously but rapidly mimic, and synchronize with, the facial expressions, movements, postures, and vocal utterances of copresent others. Second, emotions can be shaped by one's own facial expression, movement, and posture. For example, deliberately making facial expressions of fear, anger, sadness, or disgust make people likely to feel the emotion in question [21]. Third, animal researchers, historians, sociologists, and clinical, developmental, and social psychologists have produced evidence that people tend to "catch" the emotions of copresent others [20]. In sum, teammates may match each other's emotions and behaviors in a performance setting through copresence, perhaps due to the

psychosocial conditions of the common environment, emotional contagion, and their feelings toward the task at hand. By extension, this interindividual matching may contribute to collective physiological and behavioral synchrony.

1.2.2 Shared Task

A shared task may constrain action in such a way that influences the physiology of multiple individuals in similar ways, simply by virtue of the activity's metabolic or cognitive demands or other specific task constraints. For example, one might consider whether a task promotes physical exertion, synchronized breathing (e.g., singing or chanting in unison [22]), or turn taking (e.g., in conversation or anti-phase rowing) [23]. These structural characteristics of a shared task may bring about physiological synchrony unrelated to emotional or psychosocial factors. Hence, "shared task" accounts for the fact that interindividual matching of behavior may confound potential inferences about the role of shared emotion or psychosocial factors. In the context of team sports, behavior refers primarily to physical motion, such as players' direction, speed, acceleration, turning angle, etc. Due to task constraints, such as the expectation of team members to stay in formation and to move forward, backward, left, and right as a collective, individuals are likely to exhibit similar physical exertion at any given time during competition. For example, soccer teammates often walk, jog, and sprint as a collective. As a result, a team's collective behavioral synchrony (i.e., in players' movements) and collective physiological synchrony (i.e., changes in heart rate) are bound to be intertwined, due to the structural characteristics of a shared task.

1.2.3 Coordination

Coordination is defined as arranging individual behaviors in ways intended to achieve group goals [10]. In team sports, coordination is mostly a product

of visual perception [24] and communication [25], including verbal and nonverbal (e.g., eye contact, pointing, body position). This implies that team coordination involves interindividual matching both of behavior and cognition. According to the collective behavior literature, particularly that of complex systems in sports, coordination manifests as the formation of *synergies*, which are dyadic couplings between teammates, a notion derived from Hermann Haken's science of synergetics [26]. Synergies are said to form as teammates operate within task and environmental constraints [27, 28, 29] and perceive *affordances*, or possibilities for action [30]. Within a sports team, an individual may perceive affordances *for* a teammate (i.e., perceiving what the teammate can do), affordances *of* a teammate (i.e., perceiving what the teammate allows oneself to do; e.g., the teammate is open for a pass), or affordances for joint action (i.e., perceiving what multiple teammates can achieve together; e.g., a "give-and-go" play in many sports) [31]. Coordinated decision making and action is argued to be driven in large part by perceiving and acting upon shared affordances [24, 32]. Moreover, experts and novices are differentiated by the efficiency with which they detect affordances [31]. In sum, when collective members coordinate, this involves some amount of interindividual behavioral and cognitive matching, which may contribute to collective behavioral synchrony.

To summarize, each of these antecedents may bring about interindividual emotional, behavioral, or cognitive matching. Due to emotional contagion, copresence may bring about interindividual emotional matching. Interindividual behavioral matching may emanate from any of the three antecedents copresence, shared task, and coordination. Interindividual cognitive matching is a product of coordination as members of a collective communicate and perceive affordances for action. In the next section, I highlight the two major types of observable collective

synchrony – behavioral and physiological – which function as a coupled system within the conceptual framework.

1.3 The Coupled System of Collective Behavioral and Physiological Synchrony

Collective behavior, particularly in a team sports setting, pertains to physical movement and cognition (i.e., action and perception). Put another way, collective behavioral synchrony follows teammates' interindividual matching of behavior and/or cognition. On the other hand, physiological synchrony stems, in part, from interindividual emotional matching. These two forms of synchrony are inextricably linked to due to the metabolic demands of physical activity. That is, movement influences physiology, and likewise, physiological systems provide the resources needed for movement. For this reason, I have rendered collective behavioral synchrony and collective physiological synchrony as a coupled system in the framework, which is depicted in Figure 1. In this section, I elaborate on each of the two broad, observable types of collective synchrony.

1.3.1 Collective Behavioral Synchrony in Team Sports

Collective behavior refers broadly to spontaneously emerging social processes and events [33]. This includes crowd behavior, swarm behavior (e.g., of insects, flocks of birds, schools of fish, herds of tetrapods), social behavior in superorganisms (e.g., division of labor in ants or bees), and situations such as riots, fads, rumors, and other social contagion. Most relevant to this paper is the collective synchrony of human movement in team sports, although collective behavioral synchrony may be pertinent in other domains, for example, synchronous body sway in a string quartet [34]. In the coverage of collective behavior that follows, I draw primarily from human movement sciences (physical education, sport science, etc.), in particular from the literature on teams as complex systems [35].

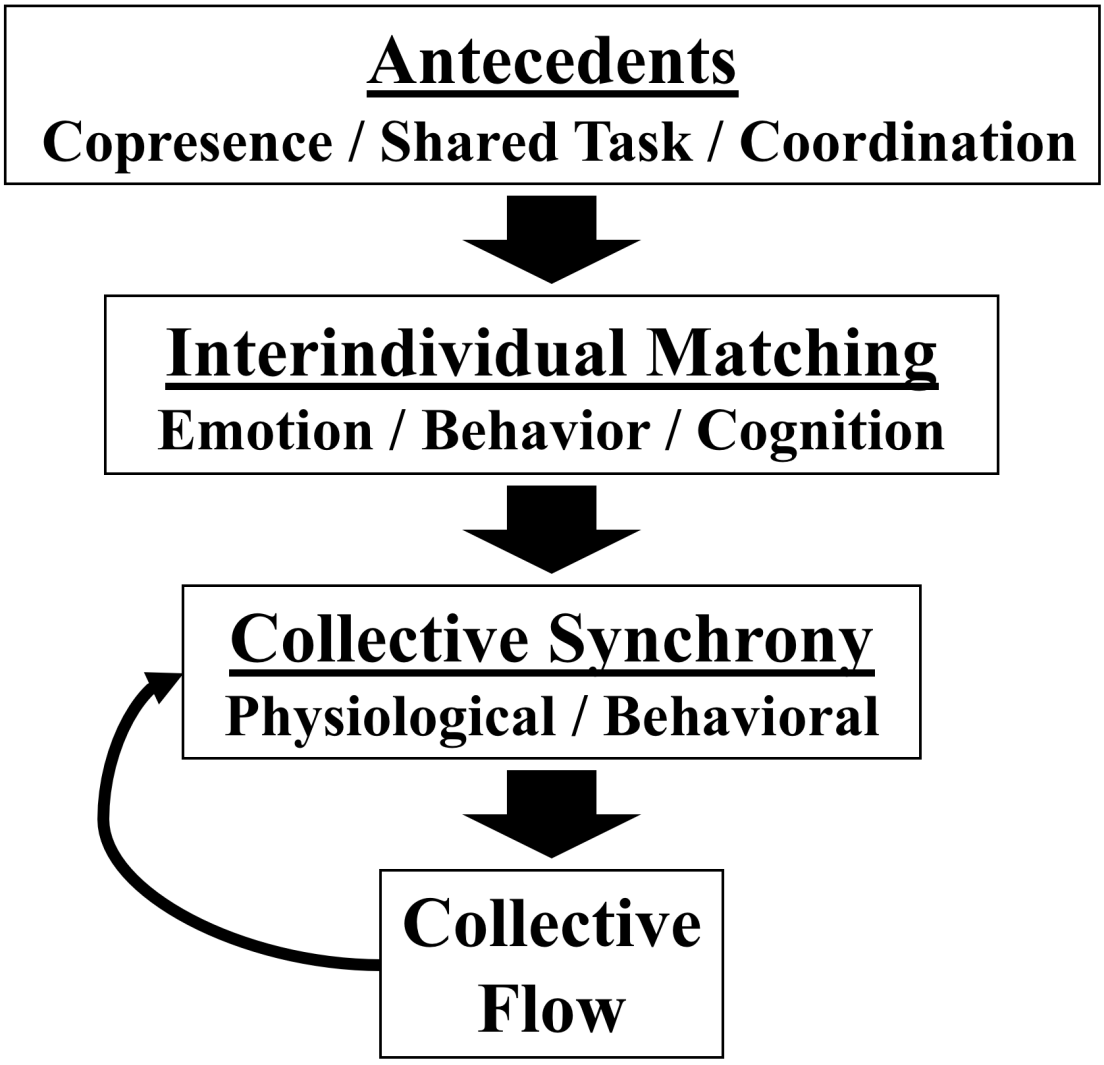

Figure 1: Conceptual framework of collective synchrony.

Central to collective behavior, and to the notion of teams as complex systems, are self-organization and the role of constraints, which are conditions or rules governing the task and environment within which a system operates [36]. Constraints may include, for example, the rules of the game; the size, shape, and other characteristics of the playing area; the number of players and whether there is a numerical imbalance; and the team formation and other tactical instructions given by the coach. A self-organizing system is one that reduces in degrees of freedom of behavior, from a large number to very few, by the formation of synergies. Within a synergy, one teammate's action influences the actions of another and vice versa [37, 38]. Self-organized collective behavior is not predetermined. Rather, governed by the constraints of the task and environment, a team's collective behavior functionally emerges to perform a goal-directed shared task through the process of self-organization [27, 28, 29]. This process reflects the arrangement of individual behaviors to meet group goals, that is, coordination. Hence, in team sports, self-organization may offer a specific explanation for how the antecedents shared task and coordination may invoke collective behavioral synchrony. In the following paragraphs, I briefly review studies to underscore the importance of collective behavioral synchrony to team sport scientists.

Collective behavior in team sports has been the focus of a number of studies in recent years, in particular with soccer teams during small-sided practice games [3, 4] or during competition [5, 6, 7]. Studies of small-sided practice games typically aim to inform coaching best practices and to examine the effects of manipulating certain constraints such as numerical imbalance. For example, two studies used GPS data to investigate collective behavior in teams of 4 players competing in unbalanced small-sided games (i.e., 4v3, 4v5, 4v7) involving amateur and professional players [3], and professional players only [4]. In both studies, an

entropy measure was used to quantify the unpredictability of (i.e., exploratory behavior exhibited by) each 4-person team's pattern of movements. Entropy was found to decrease as defensive tactics became more dominant with each increase in the numerical disadvantage. Additionally, an amateur-professional difference in entropy was reported, which suggested that amateurs have less regular positioning patterns and may rely more on additional external feedback (e.g., coaching instructions) or additional constraints to facilitate coordination [3].

Synchrony in elite men's soccer teammates' movements along the longitudinal (X) and lateral (Y) axes of the playing field were analyzed in two studies using GPS data, one including opposing teams competing in an English Premier League game [5] and one including opposing elite European teams competing in a preseason friendly game [6]. Each of these studies illuminated changes in collective behavior in different stages of the game. Investigators reported an increase in collective synchrony of movement from the first half to the second half [5]. Greater collective synchrony of movement was observed when teams were defending than when they were attacking, and synchrony decreased for both teams when the ball was closer to either goal. In another study, a new soccer team of undergraduate athletes with playing experience ranging from 0 to 15 years was assembled [7]. The aim of this study was to investigate changes, across a 15-week season, in synergies (i.e., dyadic coupling in teammates' radial distance to the goal) during movements up and down the field. Small improvements in readjustment delays (i.e., faster regulation of coordinated team actions) and increases in near-in-phase synchrony during teams' forward and backward movements were reported. In sum, collective behavioral synchrony and its antecedents are of considerable interest to scientists of team sports.

1.3.2 Collective Physiological Synchrony

Physiological synchrony is defined as temporal correspondence of multiple individuals' physiological systems [39]. This materializes when the intraindividual signals (e.g., heart rate, breathing rate, cortisol level, electrodermal activity) emanating from intraindividual physiological systems (e.g., cardiac, respiratory, glandular) become interindividually matched in time. The emergence of physiological synchrony is thought to be influenced to some degree by interindividual emotional matching, for example, due to emotional contagion among copresent individuals. Physiological synchrony appears in the literature under many names such as shared physiology or physiological attunement, coherence, compliance, concordance, coupling, covariation, entrainment, or linkage [8].

In studies of interpersonal social interaction, physiological synchrony has been linked to a number of psychosocial concepts such as emotional coregulation [40, 41, 42, 43], conflict [23, 44, 45], and empathy [46, 47]. Coregulation has been defined operationally as the "bidirectional linkage of oscillating emotional channels (subjective experience, expressive behavior, and autonomic physiology) between partners, which contributes to emotional and physiological stability for both partners in a close relationship" [41]. Similarly, the "relationships as regulators" model suggests that synchrony emerges, strengthens, and potentially stabilizes, in the behavioral, physiological, and biochemical channels of individuals in close relationships [42]. It has been argued that sexual and other intimate behaviors (e.g., embracing, cuddling) activate reward systems (i.e., opioid, oxytocin), acting as an efficient and metabolically cost-effective means by which partners regulate each other's affect and synchronize their physiological systems [43]. Ferrer and Helm [40] have provided a statistical analogue for coregulation in dyads

by proposing that it manifests as positive associations between dyad members' physiological signals.

Studies examining interpersonal conflict and physiological synchrony have reported varied results. In a study with married couples in conversation, physiological synchrony was greater when marital dissatisfaction was higher, and greater during conversations higher in conflict [44]. In contrast, during romantic partners' discussions about how they influence each other's health behaviors, relationship conflict did not predict physiological synchrony in blood pressure, inter-beat interval, or skin conductance [23]. Rather, physiological synchrony in blood pressure was found to be negative in magnitude, or anti-phase (as opposed to positive/in-phase), as a consequence of turn taking during conversation. This effect, however, was moderated in such a way that the magnitude of physiological synchrony shifted toward zero in participants reporting a more detrimental affect of their partner on health behavior. In another study, during conflict-provoking family discussions involving mother-father-adolescent triads, lagged associations in family members' cortisol responses were reported [45]. That is, mothers' cortisol predicted fathers', fathers' cortisol predicted adolescents', and adolescents' cortisol predicted mothers', at the next time point.

Empathy is one of the psychosocial constructs that has been most commonly used to explain physiological synchrony. For example, one study investigated "empathy as shared physiology" in the context of a performer, a friend, and a stranger watching a video that was mildly embarrassing for the performer [47]. Dyadic associations in skin conductance and blushing were greater in performer-friend pairs than in performer-stranger pairs. In a second experiment, strangers who had also participated in the embarrassing task blushed more than strangers who had not, presumably because they were better able to empathize with the

performer. In a study of newly formed psychiatrist-outpatient dyads, synchrony in skin conductance and patient ratings of perceived empathy were lower when the psychiatrist minimized eye contact and head nodding (i.e., emotionally distant condition) [46]. Based on these results, the investigators recommended using physiological synchrony as a potential marker of empathy in clinical settings.

Although many studies of interpersonal interactions are based on the assumption of interpersonal causality (i.e., one person's physiological signal affects that of another person), physiological synchrony may be a consequence of third variables such as experiencing a common psychosocial context (e.g., danger, embarrassment, empathy) or task (e.g., performing music, solving a problem, common movement) [8]. This is consistent with the antecedents copresence and shared task, which may lead to interindividual matching of emotion and/or behavior. The exact mechanisms underlying the emergence of physiological synchrony among multiple persons' physiology remains as an important unanswered question [8]. Additional questions include whether group members have the capacity to recognize when physiological synchrony occurs, and/or to exert control over it [8]. There is some preliminary evidence to suggest that the latter is possible. For example, Ferrer and Helm [40] found that the magnitude of synchrony in heart rate and respiration was greater in dyads who were given explicit instructions to mirror each other's physiology than in dyads under other conditions. These authors suggested that under direct instructions to synchronize their physiology, participants did so by attempting to visually observe and mimic their partners' breathing. This example highlights the coupled nature of collective behavioral and physiological synchrony. In the next section, I define collective flow and discuss it as a possible outcome of collective behavioral and physiological synchrony.

1.4 Collective Flow as a Possible Outcome of Collective Behavioral and Physiological Synchrony

Flow describes a psychological state of optimal experience that can occur in the context of many different activities such as creative pursuits (e.g., musical composition), physical or sensorimotor tasks (e.g., rock climbing, sailing, tennis), cognitive tasks (e.g., chess, mathematical problem-solving), socializing, and others [14]. According to Csíkszentmihályi and his coauthors, flow consists of nine dimensions [14, 48, 49]. The first three have been proposed as necessary conditions for flow to occur [49]. That is, flow involves a *challenging activity that requires skills* – one in which the challenges of the activity and the skills of the actor are well balanced. Flow also requires an activity in which there are *clear proximal goals* for the actor to pursue, and *immediate unambiguous feedback* about progress toward the goals is known to the actor. The remaining six dimensions are said to be characteristics of the flow experience [49]:

- *intense and focused concentration* on the present task
- *merging of action and awareness*; i.e., full absorption of the actor's attention by the activity
- *loss of self-consciousness*; i.e., freedom from self-scrutiny and social evaluation
- *sense of control* over situations that may emerge during the activity
- *transformation of time*; i.e., distortion of objective time measurement, which may be sensing the passage time to be either faster or slower than actual
- *autotelic experience*; i.e., participation in the activity is enjoyable and intrinsically rewarding

Although flow has mostly been considered an individual construct, collective flow has been examined in business or workplace settings [11, 12] and team sports [13]. Notably, Quinn [11] examined collective flow in the workplace and outlined three antecedents, two processes, and two indicators of collective flow. The first antecedent, *minimal structures* refer to norms, goals, and rules. This extends Csíkszentmihályi's dimension of clear proximal goals to account for (a) social norms that may exist within a collective, (b) collective goals that may differ from individual ones, and (c) rules governing the activity. The second antecedent suggests that there must be *comparable skills* among the individuals within a collective. Third, *introducing and embracing variation* means that collectives may intentionally introduce perturbations to keep the task challenging and/or to keep members engaged. For example, a jazz band may take turns leading. One process of collective flow is *retrospective creation of meaning*, which is described as a process of mutual adjustment, of observing feedback and responding [11, 50]. Another collective flow process is called *negotiating the "feel"*, which refers to "continual negotiation toward dynamic synchronization" [11, 51]. Whereas the former implies cognition in the mutual creation of something, the latter refers to feeling (emotionally or intuitively) the rightness or wrongness of that creation, and adjusting toward rightness (i.e., toward flow). Both of these are processes of coordination, which Quinn claims is primarily what differentiates collective flow from individual flow. Indicators of collective flow include *feeling of transcendence*, or the sense of being part of something larger than oneself, and *total preoccupation with the task*, which is analogous to Csíkszentmihályi's dimension of intense and focused concentration [11].

As collective flow is rendered above, it is highly related to the notion of interindividual emotional, behavioral, and cognitive matching, which stem from

the antecedents of collective synchrony introduced previously – copresence, shared task, and coordination. Hence, I include collective flow in the framework as a possible outcome of collective behavioral and physiological synchrony. First, emotional contagion brings about the convergence of affective states [52], which has been proposed to occur under circumstances of collective flow [11]. Quinn [11] suggested that the aforementioned process of negotiating the "feel", or mutual intuitive adjustment toward a better outcome, may happen through affective communication such as vocal intonations, raised eyebrows, and other body language. Quinn also hypothesized that the extent to which a team perceives their task as challenging should be positively associated with their collective energetic arousal (i.e., excitement), because this is the psychophysiological mechanism people use to engage in a challenging task [53]. To feel transcendence, an indicator of collective flow, is to find the activity intrinsically rewarding. This may be another source of interindividual emotional matching within a team.

Second, collective flow typically occurs in the context of a shared task, which influences interindividual behavioral matching and collective behavioral synchrony. Minimal structures (i.e., norms, goals, and rules) include task and environmental constraints, which govern collective behavior. Another precursor to collective flow, introducing and embracing variation, suggests that collectives deliberately introduce perturbations to maintain the challenge of, and engagement with, a task. This is analogous to a coach's manipulation of constraints, either during competitive games (e.g., tactical changes) or practice games (e.g., to introduce new situations to promote creative problem solving) [36, 54]. A key component of embracing variation is the presence of collective goals that outweigh those of individuals [11], reflecting another intersection with the literature on collective behavior in sports. For example, a type of division of labor known as *functional*

specialization (i.e., having various roles on a team such as starter, substitute, various positions, etc.) and altruistic cooperation (e.g., unselfishly passing to a teammate better positioned to score a goal) are characteristics of teams that reflect the prioritization of collective goals over individual goals. Functional specialization and altruistic cooperation have been highlighted in a comparison of teams and superorganisms [25].

Third, coordination is what sets collective flow apart from individual flow [11]. One of the processes of collective flow, retrospective creation of meaning, is a cognitive, creative process of mutual adjustment that involves attending to and responding to feedback [11]. This process of coordination is likely to incorporate actual communication (verbal or nonverbal) to some extent, but the coregulation that occurs within synergies is also likely to play a role. That is, shared affordances influence the actions of multiple teammates, which are coupled in synergies. In sum, coordination may bring about both interindividual behavioral and cognitive matching and is an important aspect of collective flow.

A recent contribution specific to the domain of team sports is the development of the Team Flow State Inventory (TFSI) [13]. Based on a qualitative thematic analysis of the experiences of athletes, coaches, and sport psychologists, the TFSI incorporates 14 dimensions of team flow. Of these, seven are similar to Csíkszentmihályi's individual flow dimensions, albeit modified to the context of team sport performance: challenge-skill balance, merging of action and awareness, clear goals, unambiguous feedback, concentration on the task at hand, autotelic experience, and time transformation. The other seven dimensions embedded in the TFSI are novel team flow dimensions: game plan, optimal arousal, coaching style, team communication, team confidence, external factors, and team support.

The construct of collective flow and the TFSI need further refinement.

However, the interindividual matching of emotion, behavior, and cognition, suggested in particular by Quinn's model [11], warrants the inclusion of collective flow as a possible outcome within the proposed conceptual framework of collective synchrony.

1.5 Conclusion

In this paper, I have introduced a conceptual framework of collective synchrony, into which I have incorporated ideas from multiple disciplines. The purpose of this undertaking has been to offer a starting point for investigating synchrony in team performance settings in a more comprehensive way. That is, this framework emphasizes the notion that teammates' physical movement (i.e., behavior), cognition, emotion, and physiology can become interindividually matched for a number of reasons. In particular, copresence may influence the convergence of teammates' affective states due to the psychosocial conditions of the setting, emotional contagion, and/or their feelings toward the activity. This interindividual emotional matching may bring about collective physiological synchrony to some extent. When a shared activity is goal-directed (i.e., a shared task), the structural characteristics of the task may yield interindividual behavioral matching. This may contribute to collective physiological synchrony indirectly through collective behavioral synchrony due to the metabolic demands of teammates' common physical activity, for example. Coordination may explain some degree of interindividual behavioral and cognitive matching, contributing to collective behavioral synchrony. Within this framework, I have proposed that collective behavioral and physiological synchrony are coupled systems. This is principally due to the fact that physiological systems provide the energy resources needed for human movement, and hence physiological signals respond to human movement. Finally, interindividual matching of emotion, behavior, and cognition

are apparent in the way collective flow has been conceptualized. Although at present it is not possible to directly observe collective synchrony in emotional and/or cognitive signals during team sports performance, I have decided to include collective flow as a possible outcome of collective synchrony. In sum, I posit that these elements comprise the conceptual foundations of collective synchrony.

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MANUSCRIPT 2

Collective Synchrony: A Systematic Review of the Literature

Abstract: Collective synchrony is the simultaneous occurrence of behavior, cognition, emotion, and/or physiology within a group of three or more people. In this paper, 29 studies of collective synchrony are reviewed using the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines. These studies resulted after a five-phase search and screening process. They are numbered consecutively in this paper [1] - [29]. The following characteristics of these studies were examined and are reported herein: (a) contexts, populations, and synchrony variables examined; (b) analytical methods used to quantify collective synchrony; and (c) notable findings reported. Strengths and limitations, both of the reviewed literature and the review itself, and future directions are discussed.

2.1 Introduction

In the social and behavioral sciences, *collective synchrony* refers to the simultaneous occurrence of behavior, cognition, emotion, and/or physiology within a group of people. *Collective* refers to a group of three or more people, in contrast to dyads and individuals, units which may also demonstrate synchrony. Dyads in particular have been used extensively in studies of physiological synchrony in the subdiscipline of psychophysiology. For example, synchrony in skin conductance in psychiatrist-outpatient dyads [30] and synchrony in cardiac signals of romantic couples during conversation [31] have been investigated. Synchrony may also be examined in multiple signals from an individual person. For example, neuroscientists may focus on synchrony in neural activity from multiple regions within an individual brain [32]. In contrast, collective synchrony refers to synchrony in signals of individuals grouped within a collective such as a sports team, work team, military unit, musical ensemble, dance company, group of students, family, etc.

Collective synchrony is relevant in many everyday contexts, and a multitude of scientific objectives have motivated its scientific study. In performance domains, collective synchrony in performers' voluntary movements may directly influence the quality of a performance. That is, whether dancers move, musicians play or sing, or sports teammates row, run, skate, etc. in a synchronized manner may affect an audience's rating of the performance [27] or the likelihood of victory or defeat. In sports, the notion of teams as self-organizing complex systems [33, 34] has generated interest in quantifying the extent to which players exhibit collective synchrony as they move forward, backward, left, and right on a playing field [6, 15].

Beyond movement, researchers have examined synchrony in physiological signals during other settings with coordinated tasks, for example using electroencephalography (EEG) with Navy officers-in-training performing a submarine piloting and navigation simulation [24] and copilots on a simulated flight [35]. Others have focused on synchrony in cardiovascular signals during choir singing [17, 28], during a creative construction task [9], and in research planning meetings [10]. Other contexts in which collective physiological synchrony has been investigated include families, such as cortisol response during conflict [20], and ordinary social settings, such as blushing and skin conductance while viewing an embarrassing video [21] or discussing topics of varying emotional valence [12].

Compared to voluntary movements, it is less clear what leads to collective synchrony in physiological systems, which people have very limited capacity to control and which are not coupled in any direct way. Based on existing literature on heart rate (HR) synchrony [9], in Manuscript 1 of this dissertation, three possible antecedents of collective synchrony were highlighted. First, simply being together, or *copresent*, in a situation may engender behavioral and emotional contagion such as common facial expressions and affective states, leading to common

physiological arousal. Hence, copresence refers to an emotional explanation of physiological synchrony. Second, the characteristics of a *shared task*, such as whether it constrains group members to be similarly physically active, cognitively focused, stressed, breathing rhythmically, etc., may drive collective physiological synchrony. In this explanation, it is the structural characteristics of a task that may, for example, cause team members to move similarly, and subsequently to exhibit similar physiological responses based on the metabolic demands of physical movement. Third, deliberate online *coordination* on the task, defined as arranging individual actions in ways intended to achieve group goals [36], may give rise to collective synchrony. This refers to communication, visual perception, and intentional synchronization of movement. The role of each antecedent (copresence, shared task, or coordination) is likely to be context-dependent. Understanding the role of each in various contexts such as team sports, the workplace, military applications, performing arts, etc. is an issue that merits further investigation.

To inform future studies, this paper's purpose is to present a systematic review of collective synchrony, including studies using other terminology in place of synchrony such as coherence, compliance, entrainment, linkage, and shared; e.g., "shared heart rate dynamics" [9]. The review was conducted using the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines [37]. The aims of the review are to report on (a) the contexts, populations, and synchrony variables that have been examined in studies of collective synchrony, (b) the analytical approaches that have been used to quantify collective synchrony, and (c) notable findings that have been reported in these studies. The review is organized as follows. In the next section, the methods used to procure and review the included studies are summarized. Subsequently, results are presented, including descriptive information about the studies, their contexts, populations,

variables examined, analytical methods, and notable findings. Finally, strengths, limitations, and future directions are proposed.

2.2 Method

The search and screening process was carried out in five phases as depicted in the PRISMA flow diagram (Figure 2). Phase 1 was the initial search, detailed in the next paragraph. Phase 2 was the removal of redundant search results. Phase 3 was the removal of articles deemed to be off topic or not meeting the inclusion criteria, detailed below, based on the journal title, article title, or article abstract. Phase 4 was the removal of articles not meeting the inclusion criteria, based on a review of the full text. After Phase 4, 17 articles remained for review. Phase 5 brought about the addition of 12 articles citing, or cited in, the 17 articles that remained from the initial database search. Hence, there was a final tally of 29 articles retained for this literature review. These are numbered consecutively [1]–[29] in this paper.

Phase 1 included the use of the following databases: Academic Search Complete, MEDLINE, ERIC, PsycARTICLES, PsycINFO, PubMed, and Science Direct. Titles, abstracts, and keywords were searched as follows. To ensure that search results were relevant to finding timed associations (i.e., synchrony, but possibly under one of several other names), at least one of the following terms needed to match: *attunement*, *compliance*, *concordance*, *coupling*, *covariation*, *entrainment*, *interdependence*, *linkage*, *shared*, or *synchrony*. To focus on studies using variables most often of interest in studies of synchrony, at least one of the following terms needed to match: *behavioral*, *behavioural*, *emotion*, *movement*, *performance*, or *physiological*. To help ensure that search results were relevant to collectives, at least one of the following terms needed to match: *band*, *choir*, *collective*, *company*, *crew*, *group*, *squad*, or *team*. To focus on articles that

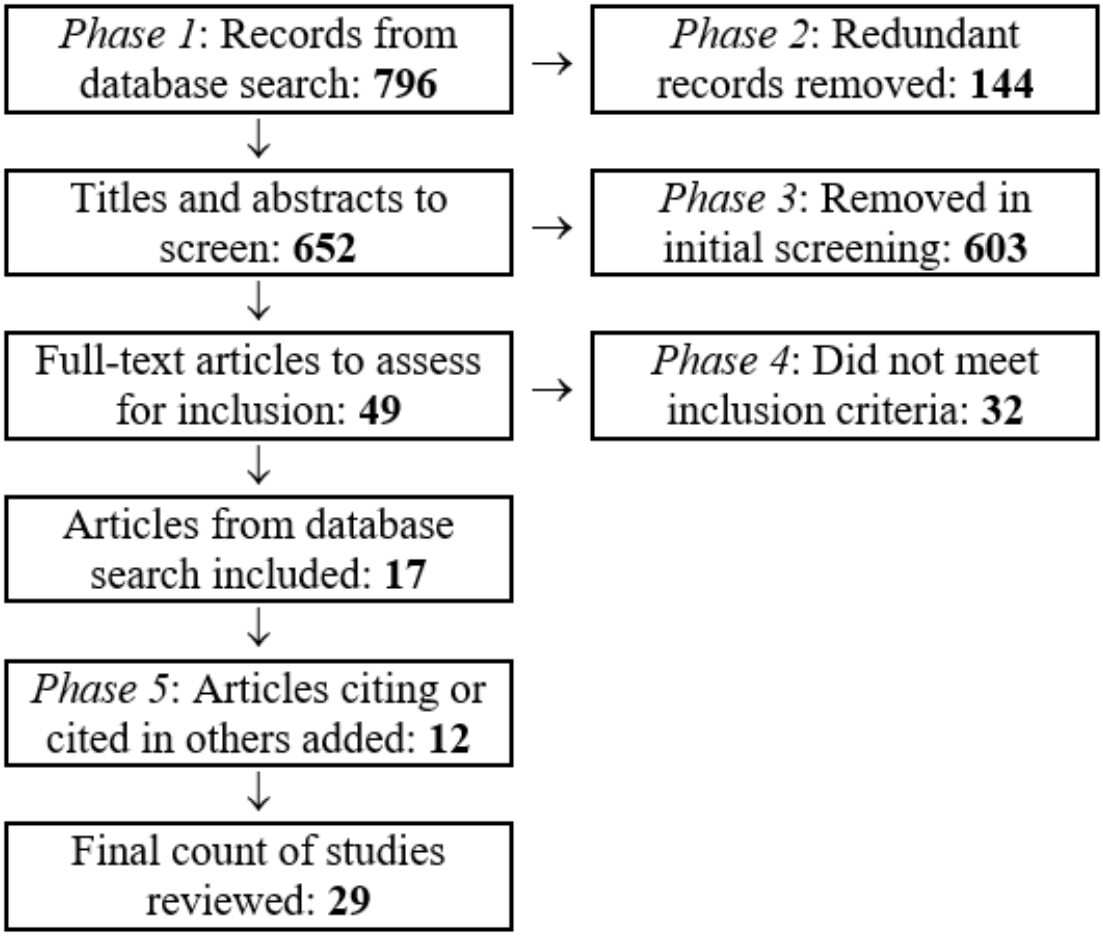

Figure 2: Flowchart of search strategy and screening.

encompassed coordinated behavior, at least one of the following terms needed to match: *cooperation*, *cooperative*, *coordinated*, *coordination*, *goal-directed*, or *joint action*. Finally, to focus primarily on certain performance settings in which collective synchrony may be of interest, at least one of the following terms needed to match: *flight*, *military*, *music*, *performing arts*, or *sport*.

The following criteria were used to screen articles in Phases 3 and 4 of the screening process. In order to be included in this systematic review, articles had to meet each of the following: (a) the article reported an empirical study, not a theoretical paper, meta-analysis, systematic review, etc.; (b) the study examined synchrony; (c) the study incorporated analysis of data streams recorded over many time points, also known as intensive longitudinal data [38]; and (d) the study incorporated collectives (i.e., groups of three or more) as the unit of analysis, not only dyads or individuals.

For each of the 29 studies included in this review, the following characteristics were examined: the contexts and populations investigated, the variables analyzed for synchrony, the analytical methods employed, and notable findings. The rationale for emphasizing these elements in this review was to illustrate the range of substantive foci of these studies, particularly in terms of the settings, populations, and variables of interest; to categorize analytical methods that have been used and identify opportunities for new methods; and to integrate common findings as well as reveal unique findings. The results of the review are reported next.

2.3 Results

The 29 studies in this review were published in years spanning from 1963 to 2018 (median: 2013, mean: 2010, standard deviation: 10.8 years). The overall recency of these studies can be attributed in part to the proliferation of technologies able to track a person's motion, physiology, and even self-reported information

(e.g., affective states) intensively over time. In these studies, data were collected in a variety of locations worldwide, including ten studies from the United States [7, 10, 13, 14, 16, 18, 20, 21, 23, 24]; five from the United Kingdom [5, 6, 25, 26, 27]; two each from France [1, 2] and Israel [8, 29]; and one each from Canada [3], Denmark [9], Europe unspecified [15], Finland [12], Germany [17], Italy [4], Japan [11], New Zealand [19], Portugal [22], and Sweden [28].

2.3.1 Contexts, Populations, and Synchrony Variables Examined

The various contexts reflected by these studies are broadly categorized as follows: team sports and group exercise, performing arts, work and military teams, families, and other. Within each of these subheadings, the populations and synchrony variables examined in each of the 29 studies are summarized next.

Team Sports and Group Exercise

Team sports and group exercise were the focus of eight of the reviewed studies [2, 5, 6, 11, 15, 18, 22, 25]. Of these, four had participants described as elite or professional athletes. Two studies focused on synchrony in elite male soccer players' movements along the longitudinal (X) and lateral (Y) dimensions of the soccer field, captured with Global Positioning System (GPS) devices during competition [6, 15]. One study included opposing teams competing in the English Premier League [6], while the other included opposing elite European teams competing in a preseason friendly game [15]. In another study, participants were professional male cricket players [25]. The substantive focus of this study was to examine "mood linkage" – synchrony in teammates' self reported mood assessed 3 times per day over the course of a four-day competition – and its relationship with players' subjective ratings of performance. In a study consisting of two experiments, participants included elite male university rugby players and

a mixed gender sample of university student volunteers [5]. In these experiments, synchrony was not measured, but rather, it was experimentally manipulated as the independent variable. Each participant was prompted to exercise in time with a metronome beat set to be the same as (synchrony condition) or different from (asynchrony condition) that of an exercise partner. The objectives were to examine the effect of synchronous rowing on social bonding assessed using a cooperative economic game that followed the rowing task (Experiment 1 with student volunteers), and to examine the effect of synchronous warm-up exercise on subsequent performance on a rugby-specific anaerobic endurance test (Experiment 2 with rugby team members).

Two other studies in a team sports context [2, 22] included athletes with lower levels of expertise. Participants in one study were French male basketball players on two under-18 youth teams; one at national level deemed to be the "expert team" and the other at provincial level deemed to be the "novice team" [2]. In this study, the synchrony variable examined was shared awareness, defined as multiple team members having a similar awareness of what is happening in the performance setting. To examine shared awareness, qualitative phenomenological data was collected from each team member and coded for activity components (i.e., action, involvement, expectations, and knowledge) and the team member(s) involved. In another study, participants were members of a newly formed soccer team made up of undergraduates in a school of sport, whose experience playing organized soccer ranged from 0 to 15 years [22]. The objective of this study was to investigate changes, over 15 weeks of weekly practices and games, in synergies in players' radial distance to the goal during movements forwards and backwards during competition. The notion of a synergy comes from Hermann Haken's science of synergetics [39], which explains the formation of self-organizing systems. Synergies

were examined as dyadic couplings between teammates (i.e., up to $\frac{n(n-1)}{2}$ or 45 couplings for the 10 outfield players on a soccer team) [22].

One of the studies described above incorporated group exercise tasks, including one experiment with elite rugby players [5]. Two other papers were in the context of group exercise including group walking [11] and Kundalini yoga and meditation [18]. In the former, coordinated walking groups of healthy, right-handed students at a Japanese university were randomly assembled [11]. Here, the variables of interest were stepping synchrony and inter-subject neural synchrony of prefrontal cortex activity measured using functional near-infrared spectroscopy (fNIRS). In the study on yoga and meditation, characteristics of the sample were not made clear, but it was implied that the participants were recruited from 11 yoga groups (4-7 participants per yoga session) over a 10-month period [18]. In this study, it was predicted that coordinated breathing in Kundalini yoga practice would produce synchrony in participants' R-R intervals (i.e., time between heartbeats).

Performing Arts

Performing arts, including music and dance, were the context studied in six of the reviewed studies [1, 3, 14, 17, 27, 28]. Similar to the studies from sport and exercise, there existed tremendous variability in expertise apparent in these studies' participants. Samples included internationally recognized professional string ensembles [3], professional dancers [27] and dancers whose level of expertise was not reported [1], amateur choir singers [17, 28], and elementary school music classes [14].

In a study of two professional string quartets, the variable of interest was body sway during performance [3]. The authors sought to answer the question: do quartet members follow each other in terms of body sway, whether or not

they see each other, and whether or not one member is designated as the leader? Both of the studies with dancers [1, 27] were interested not only in synchrony observed in the dancers themselves, but also in its effect on audience members. In one of these studies, the objective was to examine how synchrony in professional dancers' movements, monitored by wrist-worn accelerometers during live performance, would affect audience members' arousal (i.e., HR), aesthetic evaluation, and enjoyment [27]. In the other study including dancers, the purpose was to investigate whether synchrony would emerge between audience members and dancers performing a slow, nonrhythmic dance in duets, both in terms of respiration rate and heart rate (i.e., physiological entrainment) and time distortion (i.e., cognitive entrainment) [1]. Both of the studies involving choir singing [17, 28] investigated synchrony in choir members' respiration and heart rate variability (HRV) during singing. Finally, in the context of elementary school music class, one study included second to sixth grade students, racially diverse and of mixed gender, who were randomly assigned to 10 groups (2 per grade level) of 8-12 students per group [14]. In these groups, each student rhythmically played a percussion instrument, constructed specifically for this study, to record a signal showing when the instrument was struck. It was hypothesized that the ability to rhythmically synchronize would be correlated with attentional ability measured by the Strengths and Weaknesses of ADHD Symptoms and Normal Behavior Scale.

Work and Military Teams

Work and military teams were examined in six of the studies [7, 9, 10, 23, 24, 26]. This category encompasses a variety of settings including military training [7, 24], research planning [10], creative construction [9], typical workplace activities of nurses and accountants [26], and various teamwork contexts including healthcare, military, and high school science teams [23]. Although the military context could

be considered as a separate category, the small number of studies and the inclusion of military alongside other types of teams in one study [23] led to the decision to treat various workplace settings and military as a single category. Similar to team sports, group exercise, and performing arts, work and military teams tend to refer to groups that are engaged in various coordinated, goal-directed tasks.

In one study [7], young adult males with no formal combat or weapons training completed a military training exercise in randomly assigned teams of four. The study's objective was to explore the relationship between synchrony in team members' HRV and team performance. Participants in another study [24] were students in the Submarine Officer Advanced Course at the U.S. Navy Submarine School, in teams of 11 or 12. The purpose of this study was to examine cognitive neurophysiologic synchrony in EEG signals during Submarine Piloting and Navigation simulations. In a study by the same first and second authors, again the focus was on neurophysiologic synchrony in EEG, this time with military, healthcare, and high school science teams [23]. However, specific details about these samples were not reported [23]. In a study examining an academic research setting, an already existing graduate student research team of two men and two women were observed during 20 planning meetings of a six-month period to assess whether HRV synchrony could predict teamwork effectiveness [10]. In another study [9], a mixed gender sample of university students were randomly assigned to six teams of 4 or 5 members and given a creative LEGO® construction task. The objective of this study was to examine synchrony in teams' HR dynamics and, in particular, how this would be influenced by manipulating various aspects of the task and behavioral coordination, and what effect HR synchrony would have on members' perceptions of relatedness and group performance. Finally, similar to the study on mood linkage in professional cricket players described above [25], in

another study by Totterdell and colleagues [26] mood linkage was investigated in 13 teams of nurses and one team of accountants in their usual workplaces. That is, the purpose was to examine whether individuals' moods are influenced by the collective mood of their work teammates over time.

Families

Families were the focus of three studies [8, 20, 29], each with unique substantive aims. In one study [8], synchrony was examined in affective states of 100 mother-father-infant triads, each consisting of an educated, employed, middle-class, married couple and their first born child. In videotaped interactions, parents' and infants' affective states were coded in one-second frames, and these data were used to examine mother-infant and father-infant affective synchrony. In another study [20], participants were a diverse sample of 103 parent-parent-adolescent triads. The variable of interest was concordance in family members' stress response (i.e., cortisol levels) during a conflict-provoking family discussion. Whereas that study was conducted in a laboratory setting, and the videotaped parent-infant interactions in the study mentioned previously [8] were held during home visits, in a third study [29] self-reported data from the daily lives of high school girls, their mothers, sisters, and close friends living in an urban community were incorporated. This study sought to examine synchrony in menstrual cycles, in particular to compare the degree of synchrony across particular pairs (i.e., high school girls paired with a close friend, mother, sister sleeping in the same bedroom, sister sleeping in a different bedroom) as well as menstrual synchrony within 38 triads of mothers and two daughters.

Other

Other miscellaneous contexts were investigated in six of the studies [4, 12, 13, 16, 19, 21]. These consisted of randomly assembled groups of participants in experimental settings engaged together in tasks such as having a conversation, viewing a video, performing simple movements, etc. Of these studies, all but one [19] focused on some form of physiological collective synchrony. In that investigation, similar to one of the studies mentioned previously [5], synchrony was experimentally manipulated [19]. Randomly assigned groups of adult volunteers, recruited from the vicinity of a college campus, were asked to perform simple movements in time with a metronome beat that was either synchronous or asynchronous to that of other group members. Subsequent cooperative behavior was measured as the dependent variable.

In one study investigating physiological synchrony, university students of traditional age were randomly assigned to either a group of ten people tested together while seated in a circle ("collective group") or a group of ten people tested separately ("individual group") [4]. The purpose of this study was to examine whether greater synchrony – in heartbeat, respiration, and arm movements – would emerge in collectives than in individual groups across five conditions: initial baseline, spontaneous movement, music-associated movement, metronome-associated movement, and final baseline. In another study [12], physiological (HR) synchrony was investigated in a mixed gender sample of university students. In randomly assigned groups of four, each consisting of a dyad seated together and two other members seated individually in separate rooms, groups viewed and chatted about short video clips on the topics of religion, poverty, parkour, and climbing, which were intended to elicit varying emotional valence. Another study included peer groups of four male medical students having 45-minute conversations

about medical topics while galvanic skin response (GSR) was recorded for each participant [13]. The objective of this study was to explore the relationship between GSR synchrony and members affective orientations to one another (i.e., whether a member likes, dislikes, or is neutral toward a peer). The focus of another study [16] was synchrony in skin conductance, HR, respiration rate, and motion, examined in two randomly assigned audiences of 13 or 14 men aged 25-35 years. This study's purpose was to examine whether physiological synchrony in an audience would differ when viewing a TV commercial out of context versus in the context of a TV show, and when viewed in the context of a successful or unsuccessful network comedy. Finally, synchrony in skin conductance and blushing, monitored by cheek sensors, was investigated in friends and strangers to explore the notion of empathy as shared physiology [21]. Same-gender performer-friend-stranger triads of undergraduates were formed, and together they viewed an embarrassing video of the performer singing the national anthem. A second experiment attempted to produce a more empathetic physiological response from the stranger by having the stranger perform the embarrassing task before viewing another performer's video together with the performer and his/her friend.

2.3.2 Analytical Methods Used

Various methods were used to analyze collective synchrony in these studies, owing to the diverse substantive goals of the research summarized in the previous section and, perhaps, due to different preferences for particular approaches such as time domain or frequency domain time series methods, methods from dynamical systems theory, and miscellaneous others. Specific examples are cited within these subheadings below. Although numerous additional methods were used to analyze associations between collective synchrony and experimental conditions or other variables (e.g., chi-square analysis [13], correlation [1], ANOVA [11, 17, 19],

MANOVA [4], path analysis [19], linear mixed models [5, 12, 15], regression [10], Granger causality [27], and entropy [6, 24]), the methods highlighted below are limited to those used to quantify the extent to which collective synchrony was present in signals from multiple participants.

Time Domain Time Series Methods

The most common approach was to use bivariate correlations between time series for each pairwise combination of subjects, or cross-correlation, which was used in six of the studies [7, 8, 10, 12, 13, 21]. In the study [10] examining HRV synchrony during planning meetings with a research team of four graduate students (A, B, C, D), a correlation coefficient was computed for each pairwise combination (AB, AC, AD, BC, BD, CD). These coefficients were then aggregated by computing the mean for the entire meeting duration, or for particular time intervals such as when particular individuals were speaking. For example, when person C was speaking, a composite score was computed as the mean of only correlation coefficients including person C (AC, BC, CD). Similar approaches of computing bivariate correlations for each possible dyad and then aggregating as a mean value for the collective were used in two of the other studies [7, 12]. In a further two studies, the substantive focus was on particular dyad combinations within triads, that is, mother-infant and father-infant dyads [8], and performer-friend and performer-stranger dyads [21]. Therefore, in each of these studies, the third possible dyad combination was not considered, nor were the correlation coefficients aggregated as a composite for the whole collective.

Granger causality was used in two studies [3, 17]. Granger causality [40] accounts for lagged relationships in interdependent time series. It quantifies how well one time series predicts a second time series, after accounting for how well a time series predicts itself (i.e., autocorrelation). Granger causality was well suited

to determining whether string quartet members followed each other's body sway, in particular when one member was designated as the leader [3]. For example, to assess person A's influence on person B, Granger causality was computed as the log-likelihood ratio of the degree to which A predicts B, over and above the degree to which B predicts itself, conditional upon time series C and D.

Pooled time series analysis was applied to examine mood linkage within work teams and professional cricket teams, respectively [25, 26]. In pooled time series analysis, all subjects' time series (e.g., vectors of self-reported moods) are concatenated, or stacked, into one "supervector" [41]. In these studies, the mean mood score for each team, averaged over all days, and the mean mood score for each day, averaged over all teams, were included as independent variables to test associations between team and individual mood.

Linear mixed models were used to quantify synchrony in two of the studies [1, 20]. For example, to investigate whether the breathing rates of audience members were linked to that of dancers, a linear mixed model was run for each spectator [1]. The breathing rate of the spectator at each time point was regressed on the breathing rates of the two dancers in the duet at the same time points. In the study examining conflict in parent-parent-adolescent triads, time-lagged multilevel models were used to examine whether a family member's cortisol response was predicted by the other two family members' cortisol responses at the previous time point, while also controlling for autocorrelation in the person's own cortisol response [20]. In this study, three separate models for each family were run to predict time series of cortisol response for the mother, father, and adolescent.

Frequency Domain Time Series Methods

Several examples of frequency domain time series analysis were represented in these studies. All of these can be considered to fall within the umbrella of

coherence methods. In one of the articles reviewed [28], coherence is characterized as a frequency domain statistic summarizing the correlation of two signals at each frequency. Specific variants of coherence analysis used in these studies include wavelet coherence analysis, used in three studies [11, 17, 18]; generalized partial directed coherence (GPDC), used in one study [4]; and simply, coherence, used in another study [28].

Wavelet coherence analysis enables the decomposition of a time series into time-frequency space in order to determine both the dominant modes of variability and how those modes vary in time [42]. It is described as a method for measuring cross-correlation between time series as a function of frequency [11]. That is, it allows extracting the local correlation between two time series for each frequency. Further, it is a way to quantify the time evolution of spectral components of a time series [18]. Focusing on coherence in participants' R-R signals during Kundalini yoga practice, synchrony was analyzed in dyadic combinations of participants using pairwise wavelet coherence analysis, as well as in collectives using N signals wavelet coherence analysis [18]. In the study investigating neural synchrony of the prefrontal cortex in coordinated walking groups [11], pairwise wavelet coherence values for periods ranging from 10 to 85 seconds (i.e., .012 to .1 Hz) were calculated for each dyadic combination of participants, then averaged over all dyads. Similarly, in another study [17], coherence in each variable of interest, HRV and respiration rate, was computed in the frequency range 0 to 2 Hz, in .002-Hz steps, for all pairwise combinations of choir members. In that same vein, other investigators [28] analyzed bivariate coherence in HRV across a range of frequencies during choir singing, using the cross-spectral densities for each pair of participants, before taking the mean of all pairwise coherence scores.

GPDC [43], a multivariate coherence method, was utilized to examine

collective synchrony in arm movements, heartbeat, and respiration among 10 group members in an experimental setting [4]. These authors describe GPDC as a frequency domain approach to assess the intensity and direction of information flow in multivariate time series by decomposing multivariate partial coherences computed from multivariate autoregressive models. Akin to some of the above examples, GPDC is used to find relationships in each pairwise combination of signals. However, it does so in the context of a multivariate model that considers all participants' signals simultaneously. That is, the computation of each pairwise coherence takes into account the influence of the remaining $N - 2$ signals. GPDC also considers forward and backward influences between time series, based on the concept of Granger causality.

Methods from Dynamical Systems Theory

Nonlinear methods often associated with dynamical systems theory were used in several of these studies. These include methods for analyzing phase synchrony in oscillating time series (i.e., waves) [44], such as relative phase used in one study [22], cluster phase used in two others [6, 15], and vector strength used in another study [14]. Other methods include cross recurrence quantification analysis (CRQA) used in two studies [9, 27] and Shannon entropy used in one study [23].

Methods based on the phase difference between two waves, expressed in degrees or radians, that is, the extent to which waves are in phase or out of phase with each other, were employed in each of the three studies examining synchrony in the movements of soccer teammates [6, 15, 22]. Relative phase, widely used in signal processing, considers pairwise combinations of time series to be the output of coupled oscillators and expresses their synchrony in terms of their phase difference [44]. This approach was used to identify epochs of near-in-phase synchrony (i.e., relative phase between -30°and 30°) in dyads' distance to

goal measures [22]. At times of near-in-phase synchrony, teammate dyads were categorized as strongly coupled (i.e., synergies) in this study. Extending phase synchrony from dyads to collectives is the cluster phase method [45, 46], which was used to quantify collective synchrony in teammates' movements along the X and Y dimensions of the soccer field [6, 15]. Cluster phase method is based on the Kuramoto order parameter [47] and involves the computation of a relative phase time series for each individual relative to the group's "cluster phase". From these, the degree of collective synchrony can be aggregated as the "cluster amplitude" at each time step. Cluster amplitude values can range from 0 to 1, that is, completely unsynchronized to completely synchronized. Vector strength [48], a computation similar to relative phase, was used to quantify the synchrony with which elementary students played percussion instruments [14]. Here again, vector strength for a participant would be 0 if playing randomly and 1 if playing perfectly in time with a driving beat.

CRQA [49] is a method for quantifying the shared dynamics of nonlinear systems. By reconstructing the phase space of two time series, this method helps identify the rate and length of recurrences in a dynamical system, that is, the instances in which the two time series display similar dynamics. CRQA was used to measure collective synchrony of acceleration in dancers during live performance [27]. The recurrence rate was computed for all dyadic combinations, then averaged for all pairs to represent the collective synchrony. Similarly, in another study [9] the recurrence rate was used as a proxy of the *level* of coordination in all possible group member pairs' heart rates during a creative construction task, while the average length of recurrences was used as a proxy of the *stability* of coordination.

Information entropy, or Shannon entropy [50], was used in one study [23] to quantify the degree of regularity in team members' EEG signals. The lower the

entropy, the greater the regularity in multiple time series, and hence, the greater the collective synchrony. In this study, the level of neurodynamic organization in a team was measured as the entropy in randomized data streams minus the team entropy. The lower the team entropy, the greater this difference, and the greater the neurodynamic organization (i.e., synchrony).

Other Approaches

A handful of other approaches were used to examine collective synchrony in these studies. Dynamic social network analysis was used to describe patterns of shared awareness in basketball teammates [2]. To explore how teammates connect and disconnect with one another, changes in social network characteristics, including centrality, density, reciprocity, and transitivity, were examined. Unsupervised artificial neural networks, a clustering method, was used to identify patterns in different combinations of participants (Navy submarine officers-in-training) showing below average, average, or above average task engagement based on EEG signals [24]. In another study, focusing on HRV synchrony during a military training task, several dyadic approaches, in addition to bivariate correlation noted above, were used [7]. These methods include signal matching, instantaneous derivative matching, and directional agreement. Signal matching quantifies the area between the curves of two time series of z-scores, with less area corresponding to greater synchrony. Instantaneous derivative matching measures the similarity in time point to time point changes in two time series. Directional agreement simply captures whether two time series match in terms of their direction (increasing or decreasing) at each time point. From this, the percent agreement (out of the total time series length) can be computed. A similar idea, co-occurrence, was used to quantify the proportion of total time a parent and infant matched in terms of their affective state [8]. To quantify

menstrual synchrony in families and close friends, the mean difference in the date of menstrual cycle onset was used [29]. Finally, one study [21] used ANOVA and t-tests on aggregated measures of blushing in performer-friend-stranger triads; one study [16] did not specify the method used, citing a "proprietary methodology"; and two studies [5, 19] did not quantify synchrony but rather manipulated it as a categorical independent variable.

2.3.3 Notable Findings

Having various substantive foci and methodological approaches, numerous findings were reported in these 29 studies. They are categorized here as findings that reveal positive relationships between synchrony and other variables, between-group differences in synchrony, within-group changes in synchrony across time or changing task conditions, evidence of leader-follower relationships, and expert-novice differences in synchrony.

Positive Relationships Between Synchrony and Other Variables

It was very common in these studies to report positive relationships between synchrony and other variables (e.g., performance). Several studies treated synchrony primarily as an independent variable. For example, string musicians' collective synchrony in body sway was associated with self-evaluated performance [3]. A related finding, synchrony in dancers' movements was reported to predict spectator enjoyment and HR arousal [27]. Likewise, HRV synchrony was higher in high performing teams than in low performing teams [7]. In one study [5], experimentally manipulated synchrony in rugby players' warm-up exercise was associated with subsequent anaerobic test performance. Mood linkage in cricket teams was positively associated with self-reported measures of performance, engagement in collective activity, commitment to the team,

susceptibility to emotional contagion, and age [25]. In teams of nurses, mood linkage was greater for older nurses, for higher self-reported commitment to the team and team climate, and when fewer hassles with teammates were reported [26]. Children's ability to synchronize rhythmically with others in music class predicted their attentional ability [14]. Synchrony in parent-infant affective states was associated with the complexity of the infant's symbolic play [8]. Experimentally manipulated synchrony in simple movements, combined with shared intentionality, was associated with group members' level of cooperation [19]. Finally, physiological synchrony in HR was strongly connected to participants' self-reported social presence [12].

Other studies treated synchrony primarily as a dependent variable. Spectators' attention to their own and dancers' breathing during the dance performance predicted physiological synchrony between spectators and duet members [1]. Synchrony in medical student peers' GSR was associated with the strength of affective orientation [13]. That is, participants exhibited greater synchrony with individuals they liked or disliked than with peers viewed neutrally. In a creative construction task, interpersonal speech and building coordination were shown to predict HR synchrony [9].

Finally, it is worth noting that in one study [10] surprising negative associations were reported in the context of research planning meetings. HRV synchrony during intervals in which two graduate students spoke in sequence was negatively associated with ratings of team productivity, quality of communication, and ability to work together.

Between-Group Differences in Synchrony

Several studies reported between-group differences in synchrony, primarily with randomly assigned experimental groups. In one study [11], the experimental

group walking with an audible steady beat demonstrated greater inter-subject neural synchrony and stepping synchrony. In another study, HR synchrony was greater in actual collectives engaged in the creative construction task in than in virtual pairs [9]. Similarly, participants tested in a group, although they did not have shared goals and were not given any instructions about synchronization, coupled their arm movements significantly more than groups of participants tested individually [4]. Audiences viewing a TV commercial in context (vs. out of context) and during a successful (vs. unsuccessful) network comedy exhibited greater engagement, measured in part as physiological synchrony in skin conductance, HR, respiratory rate, and motion [16]. In a study focusing on the notion of empathy as shared physiology [21], blushing synchrony while viewing a performer's embarrassing video was greater in performer-friend dyads than in performer-stranger dyads in experiment 1. In experiment 2, strangers who had participated in the embarrassing task blushed more while watching another performer's embarrassing video than strangers who had not; or who had, but were assigned to watch a neutral video. Finally, in one study with naturally existing groups, greater menstrual synchrony was reported in mother-daughter-daughter triads and in dyads of daughters sleeping in the same room, compared to girls and their close friends not living together [29].

Within-Group Changes in Synchrony

Several studies reported within-group changes in synchrony over time (e.g., practice effects) or due to changing task conditions. A practice effect was observed where groups' movement synchrony occurred immediately in the presence of a task-irrelevant metronome cue and extended to an uncued condition the next day [4]. Similarly, HR synchrony increased over repeated trials of a creative construction task [9]. Another study examined whether a newly formed soccer team would show

practice effects in synergy formation over 15 weeks of observation with weekly practices and games [22]. Small improvements in near-in-phase synchrony during teams' forward and backward movements and in readjustment delays (i.e., faster regulation of coordinated team actions) were reported. Each of the other two soccer team studies [6, 15] highlighted changes in collective movement synchrony in different parts of the game. In one [6], an increase in the second half, compared to the first half, was reported. In the other [15], greater collective movement synchrony was observed when teams were on defense, compared to offense, and decreases were observed for both teams when the ball was closer to either goal. Each of the choir studies [17, 28] reported within-group changes in physiological synchrony in response to changes in song structure. An increase in HRV and respiration synchrony was observed during singing, compared to rest, and when singing in unison, compared to singing a song with multiple voice parts [17]. Similarly, there was a clear tendency for HRV synchrony as people chant or sing in unison [28]. Synchrony in choir members' HRV was higher while chanting a mantra with guided breathing than all other conditions, and higher during hymn singing than in the humming and baseline conditions. Finally, changes in neurophysiological synchrony in teams of Navy officers-in-training were associated with changes in the task, such as decreases in synchrony at times when the team was stressed [24].

Leader-Follower Relationships

Three studies investigated lagged relationships to assess whether leaders and followers existed within a collective. Dynamic social network analysis of basketball teammates' shared awareness revealed that, in each team, one member often heeded or was heeded by his teammates, suggesting a leadership role in team coordination [2]. String quartet members who were secretly assigned as leaders

exerted greater body sway influence on, and were less influenced by, other members, who were not aware that a leader had been assigned [3]. Finally, there were lagged associations in family members' cortisol responses during conflict-oriented discussions [20]. Mothers' cortisol predicted fathers' at the next time point; fathers' cortisol predicted adolescents' at the next time point; and adolescents' cortisol predicted mothers' at the next time point. These associations were weaker in triads with a stepparent.

Expert-Novice Differences in Synchrony

Two studies reported findings that suggested an effect of expertise on collective synchrony. Compared to a novice basketball team, an expert basketball team demonstrated lower awareness of teammates, possibly explained by coordination processes existing more implicitly in expert teams [2]. The expert team also exhibited less intra-team variability of awareness. The authors offered the possible explanation that experts are better able to achieve and maintain an optimal level of awareness during performance. Neurophysiologic synchrony of EEG signals was lower in experienced military and healthcare teams than in less experienced teams [23]. This was consistent with the authors' hypothesis, explained as an inexperienced team's need to expend more energy over time restructuring to minimize uncertainty in the work environment.

2.4 Discussion

In this section, strengths and limitations, both of the 29 studies reviewed and the review itself, are summarized, and future directions, both substantive and methodological, are proposed. Tremendous variability is apparent in the reviewed literature in terms of the elements reported above. This may be considered both a strength and a limitation of the literature as a whole. The variety of substantive

foci and methodological approaches is not surprising due to the fact that these studies span many disciplines including advertising, anthropology, biomedical engineering, cognitive science, ergonomics, kinesiology, medicine, neuroscience, performing arts, and several areas within psychology (developmental, health, organizational, physiological, and social). On the one hand, the multidisciplinary nature of collective synchrony is a strength because it allows the cross-fertilization of research questions, study designs, and methods of analysis. On the other hand, the uniqueness of each study – in terms of context, task, population sampled, variables studied, methods of data collection and processing, and methods for quantifying collective synchrony – makes it a challenge to establish findings that can be generalized more broadly and to achieve consistency in how collective synchrony is quantified. For example, some investigators prefer the methods of dynamical systems theory, while others tend to employ time domain or frequency domain time series techniques.

The underrepresentation of female participants, particularly in team sports and some other performance settings is another limitation of the 29 studies reviewed. Of these, sixteen studies had mixed gender samples, and four did not report the gender composition of their samples, which is a limitation in and of itself. Of the remaining nine, eight had male participants only, including five studies of team sports (basketball, cricket, rugby, and soccer), one involving military training, one with groups of medical students, and one in which a sample of all men viewed a TV advertisement. The only all-female sample in the articles reviewed was the one on menstrual synchrony [29]. Apart from this, the only sample that was predominantly female was the group of nurses [26], with 62 females out of 65.

Another limitation relates to the approach taken by many of the studies to quantify collective synchrony. As it is apparent in the above subsection on

analytical approaches, investigators tended to use methods that analyzed pairwise relationships in dyadic combinations of group members. Although this approach matched the substantive aims of some studies seeking to examine particular dyadic combinations (e.g., mother-infant and father-infant dyads [8]), this approach was also taken in some studies whose sole focus was on synchrony in the collective. A common strategy was to quantify synchrony in all pairwise combinations of participants (e.g., six possible combinations in a group of four), and then simply averaging these values to obtain a composite measure of collective synchrony. This is perhaps more a limitation of the availability or accessibility of existing methods for collective synchrony than of the studies themselves.

Strengths and limitations of this review relate primarily to the search and screening process, which, as an advantage, returned a wide range of synchrony studies in terms of context, substantive focus, synchrony variables examined, and methods used. As a disadvantage, the strict terms of the database search, that is, requiring at least one match from each of five keyword sets, may have resulted in not including some studies that may have been relevant despite the absence of these terms. However, the 17 studies remaining from the initial database search were supplemented by 12 others that had cited, or were cited in, these articles. This process returned studies reflecting a wide range of synchrony investigations in terms of the attributes emphasized in this review.

A priority for future research, substantively, should be to identify mechanisms underlying collective synchrony, particularly in group members' physiological signals, an issue that was raised in this paper's Introduction. That is, an important future direction would be to control for copresence, shared task characteristics, and/or online coordination, in order to parse the effect of each. For example, to what extent is collective synchrony in physiology a product of interindividual

emotional or cognitive matching, and not simply an outcome of the metabolic demands of physical exertion? This would be valuable in helping to understand why collective synchrony materializes in various contexts.

In terms of methodology, multivariate approaches are needed to enable quantifying collective synchrony in a more elegant way than simply averaging bivariate relationships. Methods that quantify collective synchrony on a moment-by-moment basis, generating a time series of values, as opposed to extracting a single value per time interval, would allow investigating how collective synchrony itself can evolve over time. The cluster phase method used in two of the studies in this review [6, 15] offers each of these advantages. Phase synchrony is quantified between each participant and the phase of the group (i.e., its cluster phase) instead of doing so in dyad pairs. This method results in a time series of cluster amplitudes, which quantify collective synchrony as a value between 0 and 1 at each time point. Dynamic factor analysis [51, 52, 53, 54] offers another possibility for future applications. Dynamic factor analysis is a generalization of classical (cross-sectional) factor analysis to intensive longitudinal data that captures common dependence among multiple time series. Using this approach, the collective would be treated as the unit of analysis, and collective synchrony would be operationalized as the latent structure that drives multiple time series (i.e., one univariate time series per member of the collective). Moreover, the framework of regime-switching state space models [55] could be applied to account for discrete shifts into and out of low and high synchrony states.

2.5 Conclusion

In summary, 29 studies of collective synchrony have been reviewed in this paper. Representing scholarship from a number of disciplines, this literature varies extensively on several attributes that were highlighted in this review. The

contexts of these studies were categorized broadly as team sports and group exercise, performing arts, work and military teams, families, and others. Numerous populations were studied such as elite and novice athletes, dancers and musicians of varying expertise, medical students, graduate students, undergraduates, submarine officers-in-training, nurses, accountants, parents, and children. Data streams that were analyzed for collective synchrony included motion (acceleration, body sway, GPS position, playing an instrument, stepping), functional neuroimaging (EEG, fNIRS), cardiovascular signals (HR, HRV, respiration rate), other indicators of autonomic arousal (blushing, cortisol, skin conductance), affective state, menstrual cycles, and shared awareness. Methods for quantifying collective synchrony included time domain and frequency domain approaches to time series analysis, dynamical systems approaches, and other various methods. Reported findings were categorized as positive relationships between collective synchrony and other variables, between-group differences, within-group changes in synchrony, leader-follower relationships, and expert-novice differences. In future studies, it is recommended to ensure that female participants are better represented, particularly in sports and other performance settings; to focus on mechanisms explaining why physiological synchrony emerges in collectives; and finally, to introduce methods that capture collective synchrony as opposed to averages of dyadic synchrony and account for the possibility that collective synchrony may change on a moment by moment basis.

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MANUSCRIPT 3

Collective Synchrony in Soccer Players' Movement and Physiology: A Regime-Switching Dynamic Factor Modeling Approach

Abstract: Collective synchrony refers to the simultaneous occurrence of behavior, cognition, emotion, and/or physiology within teams of three or more persons. It has been suggested that collective synchrony may emanate from the copresence of team members, from their engagement in a shared task, and from coordination enacted in pursuit of a collective goal. In this paper, a regime-switching dynamic factor analytical approach is taken to examine collective synchrony in collegiate soccer teams. First, the analytical approach is presented didactically, including the state space modeling framework in general, followed by the regime-switching dynamic factor model in particular. In Study 1, collective synchrony in women's soccer teammates' running cadence and distance covered during competitive games is examined. In Study 2, collective synchrony is investigated in men's soccer teammates' changes in heart rate during small-sided possession games. Reporting on the results of these studies, I show how features of substantive interest, such as the magnitude and prevalence of collective synchrony, can be parameterized, interpreted, and aggregated. Finally, I highlight several key findings of these studies, as well as opportunities for future research, in terms of methodological and substantive aims for advancing the study of collective synchrony.

3.1 Introduction

During team sports performance, teammates will at times exhibit similarities in various behavioral, cognitive, emotional, and physiological states. Such simultaneous occurrences are known as *synchrony* [1, 2]. Synchrony within a group of three or more persons, which typically applies in team sports, is referred to as *collective synchrony*. Teams have three key characteristics that may help explain why collective synchrony can occur. That is, during competition members of a team are *copresent* in the performance setting, they are engaged in a *shared task*, and they *coordinate* with one another to achieve a common goal. Copresence means that team members are proximal to each other and are susceptible to emotional contagion, defined as "the tendency to automatically

mimic and synchronize expressions, vocalizations, postures, and movements with those of another person and, consequently, to converge emotionally" [3]. While engaging in a shared task, team members may match each other's behaviors due to specific task constraints. For example, rowing either in-phase or anti-phase (essentially, turn taking) may be a task constraint in the context of crew. Similarly, the expectation of team members to move up and down a basketball court together as a team is a structural feature of the game which will inevitably produce some degree of collective synchrony in speed, direction of movement, and by extension due to the metabolic demands of this action, physiological outcomes such as heart rate. Finally, teammates may exhibit collective synchrony in part due to their coordination, that is, their arrangement of individual actions to achieve group goals [4]. Coordination in team sports stems primarily from visual perception [5] and both verbal and nonverbal communication such as eye contact, pointing, and body position [6]. This may also contribute to collective synchrony.

In Manuscript 1 of this dissertation, I introduced a conceptual framework proposing that the above mentioned antecedents (copresence, shared task, and coordination) each may partially explain why collective synchrony in behavior (e.g., running speed) and physiology (e.g., heart rate) materializes during team sports performance. In an actual performance setting, more than one of these elements is likely to be at play. For example, collective synchrony in teammates' heart rates may reflect common emotions to some extent, but this effect is certain to be confounded by the metabolic demands of the (shared) physical activity. A long-term aim may be to parse each antecedent in order to examine the role of each in team sports performance. The current studies are focused primarily on developing an analytical approach to investigating collective synchrony, along with substantive aims of an exploratory nature.

In this paper, I report on two empirical studies. In Study 1, I use movement data from a collegiate women's soccer team during competition to examine the extent to which team members demonstrate collective synchrony in running cadence (a measure of steps taken per unit time) and distance covered within defined time intervals. Both of these measures can be considered indicators of players' speed. Collective synchrony in these variables is useful to analyze in the context of soccer because the tendency of players to move about the playing field similarly (in terms of direction, speed, etc.) is a crucial part of team performance. In addition to investigating collective synchrony on a game by game basis, an objective is to explore whether change occurs over the course of an 18-game season (e.g., whether a practice effect materializes). In Study 2, I examine collective synchrony in heart rate using data from triads of collegiate men's soccer players engaged in 3v1 or 3v2 practice games. The purpose is to examine the extent to which moment-to-moment changes in heart rate exhibit collective synchrony among triad members. Here, it is also of interest to examine longitudinal changes in collective synchrony in triads over three distinct study sessions spaced several weeks apart. Another objective of Study 2 is to examine whether the increased cognitive demands of the 3v2 task bring about a difference in collective synchrony by comparison to a less rigorous (3v1) task. Beyond the substantive aims of these studies, the methodological objective is to explore the use of regime-switching dynamic factor analysis, within a state space modeling framework, in order to quantify collective synchrony and identify a team's discrete changes between high and low collective synchrony states. This approach enables quantifying collective synchrony's *prevalence*, that is, the proportion of time spent in a state of high collective synchrony, and the *magnitude*, or extent, of collective synchrony. In this paper, I demonstrate how these features may be interpreted from the results of a

regime-switching dynamic factor analysis.

The methodological aim of this paper is significant for several reasons. First, although studies in various disciplines have focused on synchrony in bivariate time series (e.g., from dyads), relatively few have examined synchrony in groups of three or more persons. As a result, there are several available statistical methods for dyadic applications, but there is a shortage of multivariate options that would apply to collective synchrony. The current studies are a step toward understanding collective synchrony in teams of various sizes. Second, although synchrony has been acknowledged as a transient state which necessitates statistical methods accounting for changes in synchrony over time [7], it is most common for researchers to aggregate information about synchrony in a way that ignores its temporal dynamics. In the current research, I use an approach that accommodates temporal changes between high and low collective synchrony states. Third, team sport scientists have called for methods that enable weighting each player's unique influence on collective team variables, citing emerging approaches such as cluster phase, dominant region, and self-propelled particle models, which have been used to study collective behavior in schools of fish and crowds of people [6]. As I demonstrate in this paper, the use of dynamic factor analysis allows this type of weighting by producing a factor loading that quantifies the proportion of variation in each player's signal explained by variation in a collective variable.

This paper is organized as follows. In the next section, I give an introduction to the state space modeling framework, followed by coverage of regime-switching dynamic factor analysis in particular. Subsequently, I report Studies 1 and 2 (each with Method, Results, and Discussion), followed by the Conclusion section, in which I highlight the important findings and future research directions associated with this paper. An applied simulation, in which I had previously tested the

analytical approach on data generated to have characteristics similar to the empirical data, as well as supplementary tables, figures, and R computer code are included in appendices.

3.2 Analytical Approach

3.2.1 State Space Modeling Framework

State space modeling is a framework for analyzing intensive longitudinal data (ILD), which arise when measurement occasions number in the tens, hundreds, thousands, etc. [8]. To define state space modeling, three key characteristics are notable. First, state space models are useful for modeling system dynamics, including the relationships among variables and their changes across time. Second, state space models are primarily useful when there are a large number of repeated observations across time, that is, ILD or time series data. Third, state space models refer not to a particular statistical model but rather to a framework that can be applied flexibly to deploy many types of statistical models. State space models have been described as a unified methodology for a wide range of problems in time series analysis [9] and a general model that encompasses many special cases of interest [10]. This is not unlike structural equation modeling, a framework with which state space modeling has been compared [11]. In fact, recent software advances have enabled the implementation of state space models within a structural equation modeling environment [12].

State space modeling offers several advantages over competing approaches. First, state space models can handle multiple observed and unobserved variables, much like structural equation modeling, but the former is better suited to modeling intraindividual dynamics, especially when measurement occasions (T) outnumber subjects (N) [11]. Second, many ILD models, such as time-varying regression, ARMA models, linear mixed models, and dynamic factor models, can be deployed

in state space form [13]. Third, the methods enabled by state space models are able to address a wider range of problems than more traditional approaches to time series analysis (e.g., the Box-Jenkins ARIMA method) [9]. Fourth, state space models require a lower computational burden than Laird-Ware linear mixed models, efficiency which is valuable when analyzing ILD with large T [13, 14]. Fifth, state space modeling handles three issues common in ILD applications, that is, unevenly spaced data, missing data, and forecasting.

In the name "state space modeling", "state" refers to an unobserved, or latent, variable that characterizes a dynamic system, and "space" refers to a vector space, or a collection of vectors. Put together, "state space" reflects the central component of the model, that is, a set of state vectors, one per time point, containing the latent state variables. In state space modeling it is assumed that a dynamic system's evolution over time is characterized by these state vectors, denoted in this paper as η_t. These are associated with vectors of the observed variables ($\mathbf{Y}_t$), and the nature of this relationship is defined by a loading matrix ($\mathbf{\Lambda}$). The relationship among state variables, from one time point to the next, is defined by an autoregression matrix ($\mathbf{\Phi}$). Paramount to the framework, the state vector (η_t) appears in both equations used to specify a state space model, namely the observation equation and the state equation, which are, respectively

$$\mathbf{Y}_t = \mathbf{\Lambda}\eta_t + \epsilon_t, \quad \epsilon_t \sim N(0, \mathbf{\Theta}) \tag{1}$$

$$\eta_t = \mathbf{\Phi}\eta_{t-1} + \zeta_t, \quad \zeta_t \sim N(0, \mathbf{\Psi}) \tag{2}$$

where

- $\mathbf{Y}_t$ is a $p \times 1$ vector of observations at the current time t
- η_t and η_{t-1} are $k \times 1$ state vectors at the current and previous times,

respectively

- $\mathbf{\Lambda}$ is a $p \times k$ loading matrix relating the state variables to the observed values
- ϵ_t is a $p \times 1$ vector of measurement errors with zero mean and covariance matrix $\mathbf{\Theta}$
- $\mathbf{\Phi}$ is a $k \times k$ autoregression matrix reflecting the dependence of the current state vector on the previous one
- ζ_t is a $k \times 1$ vector of innovation errors with zero mean and covariance matrix $\mathbf{\Psi}$.

Owing to the flexibility of state space modeling mentioned above, Equations 1 and 2 can be customized by defining the contents of the model matrices, in particular $\mathbf{\Lambda}$ and $\mathbf{\Phi}$. These equations can also be extended in order to estimate intercepts and regression coefficients relating a vector of covariates to either the observation vector or state vector.

The unknown parameters of a state space model are estimated using a recursive procedure called the Kalman filter [15]. In this algorithm, information about the system state vector (η_t) is updated at each time step, as a vector of observed data ($\mathbf{Y}_t$) is introduced. The Kalman filter is initiated with user-defined starting values for the state vector and its covariance matrix at $t = 0$ (i.e., $\eta_{0|0}$ and $\mathbf{P}_{0|0}$, respectively). The Kalman filter's steps are as follows:

$$\eta_{t|t-1} = \mathbf{\Phi}\eta_{t-1|t-1} \tag{3}$$

$$\mathbf{P}_{t|t-1} = \mathbf{\Phi}\mathbf{P}_{t-1|t-1}\mathbf{\Phi}' + \mathbf{\Psi} \tag{4}$$

$$\mathbf{e}_t = \mathbf{Y}_t - \mathbf{Y}_{t|t-1} = \mathbf{Y}_t - \mathbf{\Lambda}\eta_{t|t-1} \tag{5}$$

$$\mathbf{D}_t = \mathbf{\Lambda}\mathbf{P}_{t|t-1}\mathbf{\Lambda}' + \mathbf{\Theta} \tag{6}$$

$$\mathbf{K}_t = \mathbf{P}_{t|t-1}\mathbf{\Lambda}'\mathbf{D}_t^{-1} \tag{7}$$

$$\eta_{t|t} = \eta_{t|t-1} + \mathbf{K}_t\mathbf{e}_t \tag{8}$$

$$\mathbf{P}_{t|t} = (\mathbf{I} - \mathbf{K}_t\mathbf{\Lambda})\mathbf{P}_{t|t-1} \tag{9}$$

The Kalman filter proceeds at each time step by computing one-step-ahead predictions of the state vector and its covariance matrix (Equations 3 and 4), a vector of one-step-ahead prediction errors and its covariance matrix (Equations 5 and 6), and a matrix called the Kalman gain (Equation 7). Those five equations make up the "prediction step" of the Kalman filter. In Equations 8 and 9, the state vector and its covariance matrix are updated based on the one-step-ahead prediction errors and the Kalman gain matrix (note: $\mathbf{I}$ is an identity matrix). These two equations make up the "update step" of the Kalman filter. The byproducts $\mathbf{e}_t$ and $\mathbf{D}_t$, which are the one-step-ahead prediction error vector and its covariance matrix, respectively, are passed to a likelihood function known as the prediction error decomposition function [16] (Equation 10). Optimizing this function returns the model parameter estimates:

$$\frac{1}{2}\sum_{t=1}^{T}[-p\log(2\pi) - \log|\mathbf{D}_t| - \mathbf{e}_t'\mathbf{D}_t^{-1}\mathbf{e}_t] \tag{10}$$

Next, I demonstrate how a regime-switching dynamic factor model (RSDFM) can be represented as a state space model.

3.2.2 Regime-Switching Dynamic Factor Analysis

Regime-switching state space models [17] are useful for applications in which a dynamic system transitions (i.e., "switches") between two or more discrete stages (i.e., regimes). For example, this approach has been used to detect switches

between regimes of high and low pain, abrupt mood changes during a major depressive episode, and changes between high and low performance in basketball field goal attempts [18]; as well as between regimes of facial electromyography activation and nonactivation [19]. In the current studies, I use a regime-switching state space modeling approach to analyze transitions between high and low collective synchrony in soccer teammates' movement and physiology during performance.

Equations 1 and 2 can be modified as follows to reflect regime dependency, where the subscript R_t indicates matrices that may contain regime-varying parameters:

$$\mathbf{Y}_t = \mathbf{\Lambda}_{R_t}\eta_t + \epsilon_t, \quad \epsilon_t \sim N(0, \mathbf{\Theta}_{R_t}) \tag{11}$$

$$\eta_t = \mathbf{\Phi}_{R_t}\eta_{t-1} + \zeta_t, \quad \zeta_t \sim N(0, \mathbf{\Psi}_{R_t}) \tag{12}$$

Within a regime-switching paradigm, the state space framework remains flexible to fit many special cases of statistical models. Dynamic factor analysis [13, 20, 21, 22] generalizes conventional multi-subject cross-sectional factor analysis to ILD in order to capture common dependence among multiple time series. Here, the collective is treated as the unit of analysis, with collective synchrony operationalized as the latent structure that drives multiple time series (i.e., one time series per individual). A regime-switching approach is used to account for transitions between a regime of "high" collective synchrony, that is, one in which the observed time series are driven by a common latent factor; and "low" collective synchrony, that is, a regime in which there is assumed to be no correlation among the multiple time series.

The RSDFM used in the current investigations is written

$$\begin{bmatrix} y_{1t} \\ y_{2t} \\ \vdots \\ y_{pt} \end{bmatrix} = \begin{cases} \begin{bmatrix} 0 & 0 \\ 0 & 0 \\ \vdots & \vdots \\ 0 & 0 \end{bmatrix} \begin{bmatrix} C_t \\ C_{t-1} \end{bmatrix} + \begin{bmatrix} \epsilon_{1t} \\ \epsilon_{2t} \\ \vdots \\ \epsilon_{pt} \end{bmatrix}, \quad \Theta = \begin{bmatrix} \theta_{11} & & & \\ & \theta_{21} & & \\ & & \ddots & \\ & & & \theta_{p1} \end{bmatrix}; & \text{if } R_t = 1 \\ \begin{bmatrix} 1 & 0 \\ \lambda_2 & 0 \\ \vdots & \vdots \\ \lambda_p & 0 \end{bmatrix} \begin{bmatrix} C_t \\ C_{t-1} \end{bmatrix} + \begin{bmatrix} \epsilon_{1t} \\ \epsilon_{2t} \\ \vdots \\ \epsilon_{pt} \end{bmatrix}, \quad \Theta = \begin{bmatrix} \theta_{12} & & & \\ & \theta_{22} & & \\ & & \ddots & \\ & & & \theta_{p2} \end{bmatrix}; & \text{if } R_t = 2 \end{cases} \tag{13}$$

$$\begin{bmatrix} C_t \\ C_{t-1} \end{bmatrix} = \begin{bmatrix} \phi_1 & \phi_2 \\ 1 & 0 \end{bmatrix} \begin{bmatrix} C_{t-1} \\ C_{t-2} \end{bmatrix} + \begin{bmatrix} \zeta_t \\ 0 \end{bmatrix}, \quad \Psi = \begin{bmatrix} \psi & 0 \\ 0 & 0 \end{bmatrix} \tag{14}$$

where the observation vector $[y_{1t} \quad y_{2t} \quad \dots \quad y_{pt}]'$ is a multivariate time series consisting of data from p persons[1]. Regime 1 ($R_t = 1$) is defined as the "low" synchrony regime, and Regime 2 ($R_t = 2$) is defined as the "high" synchrony regime. This is apparent in the disparate loading matrices ($\mathbf{\Lambda}_{R_t}$) in Equation 13. Whereas in Regime 1 the loadings are set to zero signifying that the observations are not driven by a latent collective process, in Regime 2 the loadings are estimated parameters, with the exception of the first one being set to 1 for the purpose of scaling. Additionally, Equation 13 reflects that the measurement error variance matrix ($\mathbf{\Theta}_{R_t}$) is estimated separately for each regime.

In Equations 13 and 14, for illustration, a second-order autoregressive process, or AR(2), is specified for the collective state variable (C_t). However, these equations can be modified to specify any chosen order of process. In the studies reported in this paper, AR(1) and AR(2) models are used. To re-formulate the model depicted in Equations 13 and 14 as an AR(1) process, the state vector

[1] Although in multivariate applications the symbols p and n conventionally refer to the number of variables and persons, respectively, in this model formulation the number of time series (p) is equal to the number of persons in the collective (i.e., one time series per person). I have decided to keep with the convention of the state space modeling framework, in which the observation vector is $p \times 1$, and hence throughout this paper, p refers to the number of persons in the collective.

would become simply $[C_t]$; $\mathbf{\Phi}$ and $\mathbf{\Psi}$ would become 1×1 matrices (i.e., $[\phi_1]$ and $[\psi]$, respectively) in Equation 14; and the second column (of zeros) in each regime-dependent $\mathbf{\Lambda}$ matrix in Equation 13 would be omitted.

In order to infer the regime in which a system resides at each time point (i.e., R_t), it is necessary to specify a transition probability matrix ($\mathbf{\Pi}$), which contains values indicating the probability that the system (e.g., collective) is in a particular regime conditional upon the regime at the previous time point. This is a square matrix whose dimensions equal the number of regimes. For a two-regime model, to which the scope of this paper is limited, the transition probability matrix can be written as

$$\begin{bmatrix} \pi_{11} & \pi_{12} \\ \pi_{21} & \pi_{22} \end{bmatrix} \tag{15}$$

where each π_{ij} is the probability of Regime j at time t, given Regime i at time $t-1$, or expressed in notation, $\pi_{ij} = \Pr[R_t = j | R_{t-1} = i]$. For example, π_{11} is the probability of staying in Regime 1, while π_{12} is the probability of switching from Regime 1 to Regime 2. Hence, these values must sum to 1, and more generally, all row sums of $\mathbf{\Pi}$ must equal 1.

Estimation of the state vector and regime at each time step, as well as the model parameters, is performed using the Kim filter [17] and maximum likelihood estimation. The Kim filter is a combination of the Kalman filter [15] and the Hamilton filter [23]. In a regime-switching model, the Hamilton filter enables the probabilistic inference of the regimes, which are also unobserved, based on the behavior of the observed time series. The Kim filter deploys these algorithms in three steps. First, the Kalman filter is used to generate an estimate of the state vector and its covariance matrix. Second, the Hamilton filter is used to obtain the joint probability of Regime i at time $t-1$ and Regime j at time t (i.e., $\Pr[R_{t-1} = i, R_t = j | \mathbf{Y}_t]$), as well as the probability of Regime j at time t (i.e.,

$\Pr[R_t = j|\mathbf{Y}_t]$). Third, a so-called collapsing process combines the estimates from the first two steps. Prediction errors are obtained as byproducts of the Kim filter and passed to the prediction error decomposition function (Equation 10), which is entered into an optimization step to obtain the parameter estimates. For each iteration of the optimization routine, the Kim filter is carried out recursively for all t $(1, 2, \ldots, T)$ so that the state vector and regime probabilities have been estimated at each time step. Although a full and detailed coverage of these algorithms is beyond the scope of this paper, details can be obtained from other sources [17, 19]. The estimated parameters of the RSDFM include the factor loadings for Regime 2 $(\lambda_2, \ldots, \lambda_p)$, measurement error variances for each regime $(\theta_{11}, \ldots, \theta_{p1}, \theta_{12}, \ldots, \theta_{p2})$, one or two autoregression coefficients for the latent collective variable (ϕ_1, ϕ_2), the innovation error variance (ψ), and the natural log odds of the regime transition probabilities $(\ln(\frac{\pi_{ij}}{1-\pi_{ij}}))$.

3.2.3 Interpreting the Parameters of the RSDFM

It may be of substantive value to researchers to quantify the *magnitude* and *prevalence* of collective synchrony. Magnitude is the extent to which the individuals in a collective are synchronized in terms of the variable of interest. Within the RSDFM approach, magnitude may be interpreted from the effect sizes attributed to the individuals in a collective. Effect size refers to the proportion of variance in each observed time series explained by the collective state variable, and as such, its value may range from 0 to 1. In the current formulation of the RSDFM, effect size for each individual is equal to 1 minus the unexplained variance (i.e., measurement error variance) in Regime 2, which is also equal to the Regime 2 standardized factor loading squared. Regime 1 is formulated with zero factor loadings (i.e., no collective process driving the observed time series), and hence, should have 100% unexplained variance. That is, the confidence intervals of the

Regime 1 measurement error variances should all include 1. In sum, an effect size between 0 and 1 will be estimated for each individual for Regime 2, and this will quantify the magnitude of collective synchrony, or extent to which each individual's time series reflects the collective, within the high collective synchrony regime. Individual effect sizes can be averaged to obtain an aggregate measure of magnitude for the collective. As an alternative approximation of magnitude, and/or for comparison, the researcher may assess the correlation coefficients for all pairs of collective members (e.g., teammates) separately for each of the predicted regimes.

It may also be useful to quantify collective synchrony's prevalence, which I define as the proportion of time in which a collective resides in Regime 2 (i.e., the high collective synchrony regime). The RSDFM approach yields a prediction of Regime 1 or Regime 2 at every time point, making it straightforward to assess the prevalence of high collective synchrony. This can be easily computed as the number of time points at which Regime 2 was predicted, divided by the total number of time points. This proportion (or percentage, if reported as such) is often referred to as the *dwell time* of a system within a particular state, in this case the high collective synchrony regime. In the next sections, dwell time will be reported as the main metric of the prevalence of collective synchrony. The estimated regime transition probabilities (π_{ij}) can also indicate whether Regimes 1 and 2 are well balanced or one regime is relatively dominant over an analyzed time interval. For example, if π_{11} is estimated to be .75 and π_{22} is estimated to be .99, this suggests that Regime 2 is dominant. That is, Regime 2 is so prevalent that when the collective resides in this high collective synchrony state, there is only a .01 probability of switching to Regime 1 at the next time point. In contrast, when the collective is classified as residing in Regime 1, there is a .25 probability of switching to Regime

2. These approaches to examining and reporting the magnitude and prevalence of collective synchrony are demonstrated in the empirical studies reported in the next two sections.

Before using the RSDFM to analyze the observed time series obtained for Studies 1 and 2, I tested this method of analysis on simulated multivariate time series of known AR order and regimes. Time series were generated to show a high degree of collective synchrony within certain intervals and to have characteristics similar to the empirical data collected for Studies 1 and 2. Details of the applied simulation are provided in Appendix A. The simulation demonstrated that the RSDFM is a highly worthwhile approach for analyzing collective synchrony. The RSDFM was able to categorize the true regimes very accurately overall. Additionally, the parameter estimates returned by the analyses were as expected. In the Regime 2 intervals, the individual effect sizes were consistent with the bivariate correlations among the time series. In the Regime 1 intervals, the proportion of unexplained variance was estimated with confidence intervals containing 1 (i.e., 100% unexplained variance, as anticipated). Additionally, the estimated regime transition probabilities were consistent with the frequency of actual regime switches that were built into the simulated data. Taken together, these results demonstrate that the RSDFM is a promising approach for categorizing high and low collective synchrony and estimating parameters quantifying the magnitude and prevalence of collective synchrony present in multivariate time series. The RSDFM approach was utilized in the exploratory empirical studies (Study 1 and Study 2), which are reported in the next two sections.

3.3 Study 1: Collective Synchrony in Women's Soccer Players' Movement Behaviors

3.3.1 Method

Participants, Procedures, and Materials

Varsity women's soccer players were recruited from a National Collegiate Athletic Association (NCAA) Division I team in the United States. The university's Institutional Review Board approved the study protocol detailing the recruitment of participants and data collection procedures. The number of players who gave informed consent to participate in the study was 25. Data were collected during the team's competitive 2017 season, including all 18 regular season home and away games. Only outfield players were included in the study; goalkeepers were excluded. For each game, participants who started the game and played without substitution until halftime were included. Therefore, out of the ten outfield players starting each game, some were excluded due to first half substitutions and the fact that some starters may not have been consenting participants. The actual sample size for each of the 18 games ranged from 3 to 9 participants (median = 6). Data from the second half of games were not used due to practical issues such as the halftime break and the prevalence of second half substitutions.

In this study, the collective is the unit of analysis, and data were collected in the team's natural competitive setting without any researcher interference. That is, in each game it was solely the team's coaching staff who determined which individuals played, so the study participants vary from game to game. A unique identification code was randomly assigned to each participant for the purpose of recording which individuals started each game. However, for the purposes of the analyses performed, identities of the individuals participating in each game and their playing positions (e.g., defender, midfielder, forward) are not of interest. In terms of how the analyses were carried out, the individual participants can be assumed to be interchangeable. For example, the symbol used to represent player

4 (i.e., y_4) may, in different games, refer to different individuals. Likewise, data from the same individual may be denoted as y_1 in one game and y_3 in another game.

Data were collected using the Polar® Team Pro system (Polar Electro, Inc., Kempele, Finland). This system consists of a chest strap monitor worn by each participant and a tablet computer application with an interface that enables real-time performance tracking. The wearable devices include GPS tracking, accelerometers, and heart rate monitoring, and the data are delivered to the online application using Bluetooth technology. The system was owned and used regularly by the team during training and competitive games. Team members each had their own numbered device, and at the outset of the study all participants already had training and experience wearing the monitors properly. Data streams including acceleration, running cadence, cumulative distance, and heart rate were available for download after each game. In this study the variables of interest are cadence and distance. Data sets were downloaded following each game, then processed and analyzed, as detailed next.

Data Processing and Analysis

Running cadence data streams were recorded at a rate of 1 Hz in units of revolutions per minute (rpm), where one revolution equals two steps (e.g., 80 rpm = 160 steps per minute). Cumulative distance was recorded at 10 Hz in units of yards. The cumulative distance time series were converted to distances covered within defined time intervals, or bins, by differencing the cumulative values. Similarly, cadence time series were aggregated by taking the mean cadence within each bin. Time series were examined for order of ARMA process using plots of the autocorrelation function (ACF) and partial ACF (PACF) and by running univariate ARMA models on individual time series. The R [24] functions `acf`, `pacf`,

and `arima` were used to perform these diagnostics. If the ACF has a significant autocorrelation persisting over many lags (i.e., decays gradually as in the left-hand column of plots in Figure B.1 in Appendix B), and the PACF becomes non-significant abruptly after a smaller number of lags (i.e., as in the right-hand column of the same figure), then this is indicative of an AR process [25]. Most of the individual time series, both for cadence and distance, exhibited ACFs and PACFs similar to those illustrated in Panels B, H, J, and L of Figure B.1 with the PACF significant at the first two lags (i.e., an AR(2) process). Others were identified as AR(1) due to the PACF being non-significant at the second lag as in Panels D and F. It is for this reason that both AR(1) and AR(2) models were used in this study and in the analyses on test data reported in Appendix A.

Determining an appropriate sampling rate (i.e., bin size) for the data requires balancing a tradeoff between scientific and practical considerations. In terms of scientific considerations, it is desirable to sample data frequently enough to reflect the time scale of interest to examine changes in the observed variables [26, 27, 28]. In terms of practical considerations, data sampled very close together may have features such as repetition of the same or very similar values (i.e., high autocorrelation) and may therefore exhibit nonstationarity. Ultimately, both cadence and distance time series were aggregated in bins of 3 seconds due to issues with nonstationarity that became apparent when using bins of 1 or 2 seconds. This was evident in part by the large number of models that failed to converge. Of the models that did successfully converge, the estimated AR coefficients were very close to, and their confidence intervals covered, the boundaries of stationarity conditions. That is, for AR(1) models, the parameter ϕ_1 estimates were close to 1, and for AR(2) models, the sums of the parameter ϕ_1 and ϕ_2 estimates were close to 1. These problems were no longer apparent after reducing the sampling rate by

increasing the bin size to 3 seconds. Given that observations were taken from the first half (45 minutes) of each soccer game, using a bin size of 3 seconds yielded time series each with 900 observations. Finally, before analysis each time series was standardized, that is, converted to z-scores, which enables straightforward interpretation of each measurement error variance estimate as the proportion of variance in the observations not explained by the latent collective variable.

When analyzing the simulated test data reported in Appendix A, a two-regime RSDFM was assumed because the low and high synchrony regimes were introduced by design. In this study, it is also considered that a one-regime model, that is, a non-switching (high synchrony only) dynamic factor model (DFM), may provide better fit than the RSDFM. For all analyses, I used the **dynr** R package [29]; see Appendix C for sample R code. The variables cadence and distance were analyzed separately for each of the 18 games (i.e., 36 unique data sets). For each data set, the best fitting model was selected by comparing Akaike Information Criterion (AIC) [30] and Bayesian Information Criterion (BIC) [31] fit indices. When comparing AIC or BIC values for models fit to a given data set, smaller values indicate better model fit. In sum, one best fitting model (AR(1) DFM, AR(2) DFM, AR(1) RSDFM, or AR(2) RSDFM) was selected for each game/variable combination based on the lowest AIC/BIC value (see Tables B.1 and B.2 in Appendix B). There were some models that converged but had non-positive definite Hessian matrices, which meant that the standard errors were computed using a nearest positive definite approximation to the Hessian matrix, and hence were not trustworthy. These models were discarded and not considered for selection.

3.3.2 Results

In general, AIC and BIC were in agreement of the best fitting model for each data set, so only AIC values are displayed in Appendix B in Tables B.1 and B.2.

One exception was the analysis of cadence data from Game 17, where the AR(2) RSDFM produced the smallest AIC, while the AR(2) one-regime model produced the smallest BIC. In that case, the RSDFM was selected as indicated in Table B.1. In these tables, missing AIC values indicate models that were discarded due to untrustworthy standard errors. Examining Tables B.1 and B.2, it is clear that AR(2) models were more commonly selected than AR(1) models for both variables analyzed. One striking difference between the analyses for cadence and distance is the number of regime-switching models (RSDFMs) selected over one-regime models (DFMs). Out of the 18 selected models used to analyze cadence, there were 9 RSDFMs and 9 DFMs. Out of the 17 selected models for distance (for Game 15, no model was selected), 14 were RSDFMs and 3 were DFMs.

Next, I present detailed results of one exemplar analysis each for cadence and distance. These include the Game 7 cadence data and Game 12 distance data. In both of the examples, the AR(2) RSDFM was the selected model. Parameter estimates from the AR(2) RSDFM fit to the Game 7 cadence data can be found in Table 1. Some individual differences are apparent in the magnitudes (effect sizes) associated with individual players. That is, the collective state variable explains a higher proportion of variance in some individuals' cadence compared to others. This is reflected by the standardized loadings, which can be squared to obtain effect sizes. For example, the standardized loading associated with y_2 is .20 (i.e., effect size of .04, unexplained variance of .96 in Regime 2), which may point to this individual lacking in synchrony, in terms of cadence, with the rest of her teammates. This is also evident in Table 2, which displays the bivariate correlations in cadence time series during predicted Regime 1 ("Low"; Panel a) and predicted Regime 2 ("High"; Panel b) intervals. In Panel b, it is clear that correlations including y_2 tend to be smaller than others. As expected, the coefficients displayed

Parameter	Symbol	Est.	SE	t	95% CI	p
L1 fixed (std.)	λ_1	1.00 (.81)	-	-	-	-
L2 unstd. (std.)	λ_2	.30 (.20)	.05	6.6	(.21 , .39)	<.001
L3 unstd. (std.)	λ_3	.75 (.62)	.04	16.7	(.66 , .83)	<.001
L4 unstd. (std.)	λ_4	.90 (.70)	.04	21.1	(.82 , .98)	<.001
L5 unstd. (std.)	λ_5	1.10 (.90)	.04	29.4	(1.03 , 1.18)	<.001
L6 unstd. (std.)	λ_6	.60 (.54)	.04	13.9	(.52 , .68)	<.001
L7 unstd. (std.)	λ_7	.92 (.77)	.04	22.5	(.84 , 1.00)	<.001
MEV1 reg. 1	θ_{11}	.87	.14	6.4	(.61 , 1.14)	<.001
MEV2 reg. 1	θ_{21}	.86	.15	5.8	(.57 , 1.15)	<.001
MEV3 reg. 1	θ_{31}	1.09	.18	6.1	(.74 , 1.44)	<.001
MEV4 reg. 1	θ_{41}	.65	.11	5.8	(.43 , .87)	<.001
MEV5 reg. 1	θ_{51}	.91	.14	6.7	(.64 , 1.17)	<.001
MEV6 reg. 1	θ_{61}	1.28	.22	5.7	(.84 , 1.72)	<.001
MEV7 reg. 1	θ_{71}	1.24	.19	6.6	(.87 , 1.61)	<.001
MEV1 reg. 2	θ_{12}	.34	.02	14.0	(.29 , .39)	<.001
MEV2 reg. 2	θ_{22}	.96	.05	18.9	(.86 , 1.06)	<.001
MEV3 reg. 2	θ_{32}	.61	.04	15.8	(.54 , .69)	<.001
MEV4 reg. 2	θ_{42}	.51	.03	16.4	(.45 , .57)	<.001
MEV5 reg. 2	θ_{52}	.19	.02	11.5	(.16 , .23)	<.001
MEV6 reg. 2	θ_{62}	.71	.04	16.2	(.62 , .80)	<.001
MEV7 reg. 2	θ_{72}	.40	.03	14.5	(.35 , .46)	<.001
AR1 coefficient	ϕ_1	1.30	.05	27.8	(1.21 , 1.39)	<.001
AR2 coefficient	ϕ_2	-.49	.04	-12.5	(-.57 , -.41)	<.001
IE var.	ψ	.12	.01	8.4	(.09 , .15)	<.001
Log odds 1→1	$\ln(\frac{\pi_{11}}{1-\pi_{11}})$	1.23	.28	4.5	(.69 , 1.78)	<.001
Log odds 2→1	$\ln(\frac{\pi_{21}}{1-\pi_{21}})$	-3.38	.28	-11.9	(-3.94 , -2.82)	<.001

Note: CI = confidence interval; Est. = estimate; IE = innovation error; L = loading; MEV = measurement error variance; p = p-value; reg. = regime; SE = standard error; std. = standardized; t = Student's t test statistic; unstd. = unstandardized; var. = variance

Table 1: Parameter estimates from AR(2) RSDFM fit to Game 7 cadence data in Study 1.

	y_1	y_2	y_3	y_4	y_5	y_6
y_2	.19					
y_3	-.20	.10				
y_4	-.06	-.11	.35			
y_5	.45	.08	-.38	-.10		
y_6	.16	.19	-.06	-.11	.00	
y_7	-.27	-.25	.34	.22	-.13	-.39

(a) "Low" synchrony intervals (predicted Regime 1)

	y_1	y_2	y_3	y_4	y_5	y_6
y_2	.19					
y_3	.39	.18				
y_4	.51	.20	.51			
y_5	.74	.17	.48	.63		
y_6	.42	.11	.34	.36	.43	
y_7	.56	.16	.54	.49	.67	.33

(b) "High" synchrony intervals (predicted Regime 2)

Table 2: Correlations in cadence in Study 1 Game 7, by predicted regime.

in Table 2 tend to be higher in predicted Regime 2 intervals, compared to their Regime 1 counterparts in Panel a, which tended to be smaller and, in some cases, negative.

The log odds of the regime transition probabilities suggest that Regime 2 was dominant, according to the AR(2) RSDFM. The estimated value of -3.38 for $\ln(\frac{\pi_{21}}{1-\pi_{21}})$ equates to a probability of switching from Regime 2 to Regime 1 of only .034, and therefore, the probability of staying in the high collective synchrony Regime 2 is estimated to be .966. On the other hand, the estimated value of 1.23 for $\ln(\frac{\pi_{11}}{1-\pi_{11}})$ in Table 1 would convert to $\pi_{11} = .774$, which is not a very high probability of staying in the low collective synchrony Regime 1. The prevalence of Regime 2 is quite apparent in the top panel of Figure 3, which shows the Game 7 cadence time series superimposed on the predicted regimes. In this analysis, the team was predicted to reside in the high collective synchrony regime with a dwell time of .91 (i.e., 820 out of the 900 time points). In the bottom panel of Figure 3, the plot is zoomed in on 30 time points to show what the data look like in one predicted regime or the other. The individual time series appear to vary independently of one another when Regime 1 is predicted (white region) and show more similar patterns of variation when Regime 2 is predicted (shaded region).

Results of the analysis of Game 12 distance data, using an AR(2) RSDFM, can be found in Table 3. Unlike in the previous example, the standardized loadings are all relatively high, ranging from .57 to .87 (.32 to .75 when squared to evaluate effect size, or magnitude). This suggests a large proportion of variance in players' distance explained by the collective state variable, that is, a large magnitude of collective synchrony. The smallest of the standardized loadings (.57, or 32% explained variance) is consistent with the slightly lower correlation coefficients including y_5 in Table 4(b), although this individual difference is not as striking as

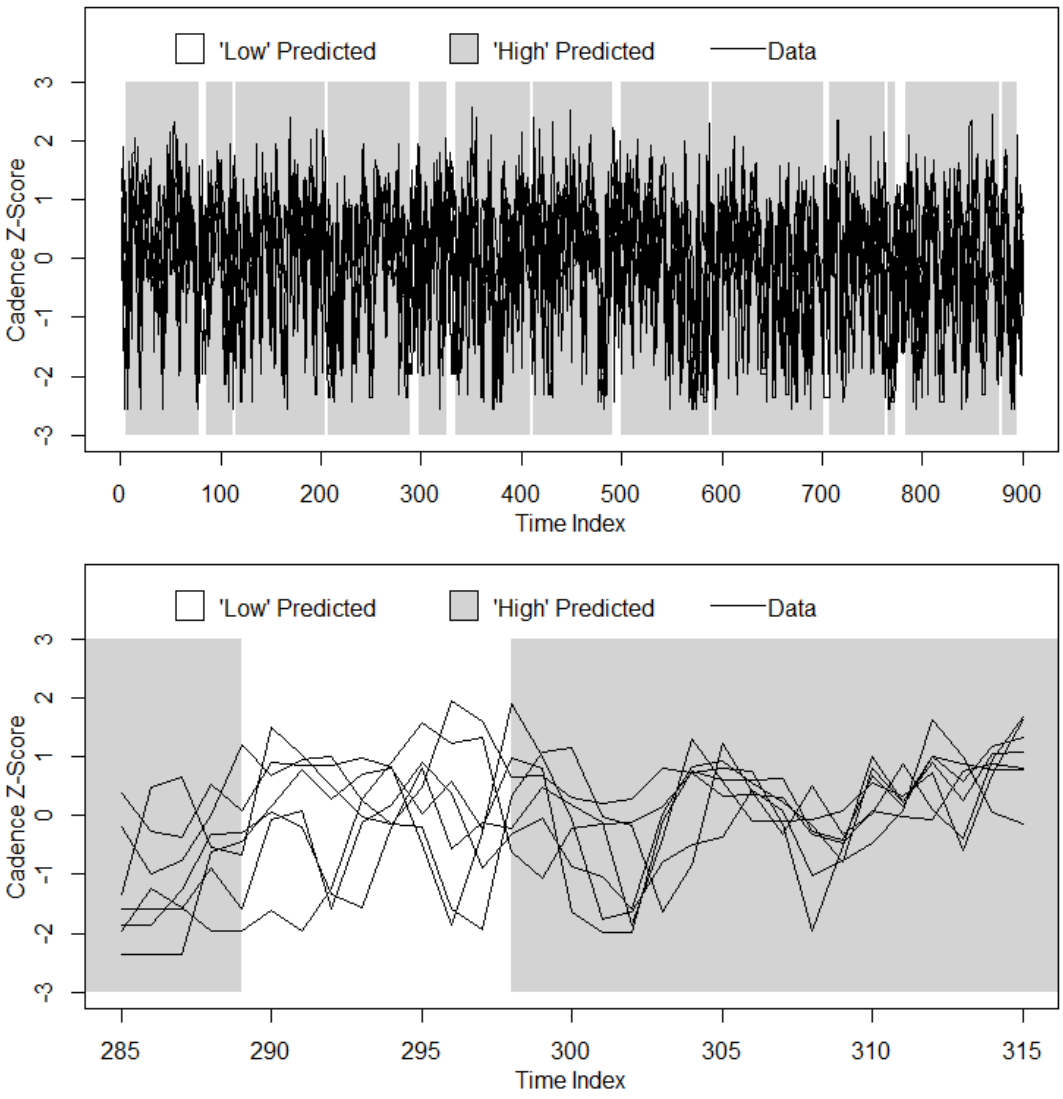

Figure 3: Study 1 Game 7 cadence data superimposed on predicted regimes; full time series (top panel) and zoomed in (bottom panel).

Parameter	Symbol	Est.	SE	t	95% CI	p
L1 fixed (std.)	λ_1	1.00 (.71)	-	-	-	-
L2 unstd. (std.)	λ_2	.94 (.81)	.05	19.7	(.84, 1.03)	<.001
L3 unstd. (std.)	λ_3	1.15 (.84)	.05	22.6	(1.05, 1.25)	<.001
L4 unstd. (std.)	λ_4	.94 (.81)	.05	2.2	(.85, 1.04)	<.001
L5 unstd. (std.)	λ_5	.81 (.57)	.05	16.0	(.71, .91)	<.001
L6 unstd. (std.)	λ_6	1.03 (.86)	.05	21.9	(.93, 1.12)	<.001
L7 unstd. (std.)	λ_7	.99 (.87)	.05	21.8	(.90, 1.08)	<.001
MEV1 reg. 1	θ_{11}	.69	.14	5.0	(.42, .96)	<.001
MEV2 reg. 1	θ_{21}	1.97	.31	6.3	(1.36, 2.59)	<.001
MEV3 reg. 1	θ_{31}	.67	.13	5.3	(.43, .92)	<.001
MEV4 reg. 1	θ_{41}	1.85	.30	6.2	(1.26, 2.43)	<.001
MEV5 reg. 1	θ_{51}	.61	.13	4.8	(.36, .85)	<.001
MEV6 reg. 1	θ_{61}	2.14	.35	6.0	(1.44, 2.83)	<.001
MEV7 reg. 1	θ_{71}	2.26	.36	6.3	(1.56, 2.96)	<.001
MEV1 reg. 2	θ_{12}	.49	.03	17.3	(.43, .54)	<.001
MEV2 reg. 2	θ_{22}	.35	.02	16.0	(.31, .40)	<.001
MEV3 reg. 2	θ_{32}	.30	.02	15.2	(.26, .34)	<.001
MEV4 reg. 2	θ_{42}	.35	.03	13.1	(.29, .40)	<.001
MEV5 reg. 2	θ_{52}	.68	.04	18.1	(.60, .75)	<.001
MEV6 reg. 2	θ_{62}	.26	.02	15.1	(.23, .30)	<.001
MEV7 reg. 2	θ_{72}	.25	.02	14.8	(.21, .28)	<.001
AR1 coefficient	ϕ_1	1.26	.04	29.4	(1.18, 1.34)	<.001
AR2 coefficient	ϕ_2	-.50	.04	-12.4	(-.58, -.42)	<.001
IE var.	ψ	.12	.01	8.8	(.10, .15)	<.001
Log odds 1→1	$\ln(\frac{\pi_{11}}{1-\pi_{11}})$	.32	.24	1.3	(-.15, .79)	.091
Log odds 2→1	$\ln(\frac{\pi_{21}}{1-\pi_{21}})$	-2.91	.19	-15.3	(-3.28, -2.53)	<.001

Note: CI = confidence interval; Est. = estimate; IE = innovation error; L = loading; MEV = measurement error variance; p = p-value; reg. = regime; SE = standard error; std. = standardized; t = Student's t test statistic; unstd. = unstandardized; var. = variance

Table 3: Parameter estimates from AR(2) RSDFM fit to Game 12 distance data in Study 1.

	y_1	y_2	y_3	y_4	y_5	y_6
y_2	.01					
y_3	.03	.14				
y_4	.22	.15	.10			
y_5	.16	-.37	-.24	.19		
y_6	.10	-.11	-.02	-.23	.00	
y_7	.18	.27	.15	.26	-.04	.07

(a) "Low" synchrony intervals (predicted Regime 1)

	y_1	y_2	y_3	y_4	y_5	y_6
y_2	.48					
y_3	.61	.64				
y_4	.52	.55	.63			
y_5	.48	.35	.48	.47		
y_6	.56	.62	.71	.57	.39	
y_7	.52	.66	.65	.73	.42	.62

(b) "High" synchrony intervals (predicted Regime 2)

Table 4: Correlations in distance in Study 1 Game 12, by predicted regime.

in the previous example. In other words, there is some indication that y_5 may not be synchronized to her teammates as well as they are to each other, in terms of distance covered in Game 12. As expected, the correlation coefficients in Table 4(a) are low and/or negative, but their counterparts in Panel b are higher and entirely positive.

As in the previous example, transition probabilities predicted by the AR(2) RSDFM for the Game 12 distance data ($\pi_{11} = .579$; $\pi_{22} = .946$), and the predicted regimes themselves (see Figure 4, top panel), show that the high collective synchrony Regime 2 is far more prevalent than Regime 1. In this example, the team was predicted to reside in Regime 2 for 857 out of 900 time points (i.e., dwell time = .95). In the bottom panel of Figure 4, the plot is zoomed in on 30 time points to juxtapose the behavior of time series in predicted Regime 1 against Regime 2. Again, the time series appear to behave more similarly in the shaded region and less so in the area with a white background.

Having inspected the results of two models in detail, next I present aggregate information about the magnitude and prevalence of collective synchrony reflected by the selected model results, across the entire season. In particular, to summarize the magnitude of collective synchrony, I focus on mean effect sizes (i.e., proportion of variance explained by the collective state variable) and bivariate correlations between teammate pairs (i.e., in low vs. high predicted regimes). To summarize the prevalence of collective synchrony, I present dwell time proportions in the high collective synchrony regime. In Figure 5, overlapping histograms depict the distribution of bivariate correlations between teammate pairs for selected regime-switching models. The histograms represent bivariate correlations from all 9 of the selected RSDFMs analyzing cadence data and all 14 of the selected RSDFMs analyzing distance data. As expected, the distributions of correlation coefficients

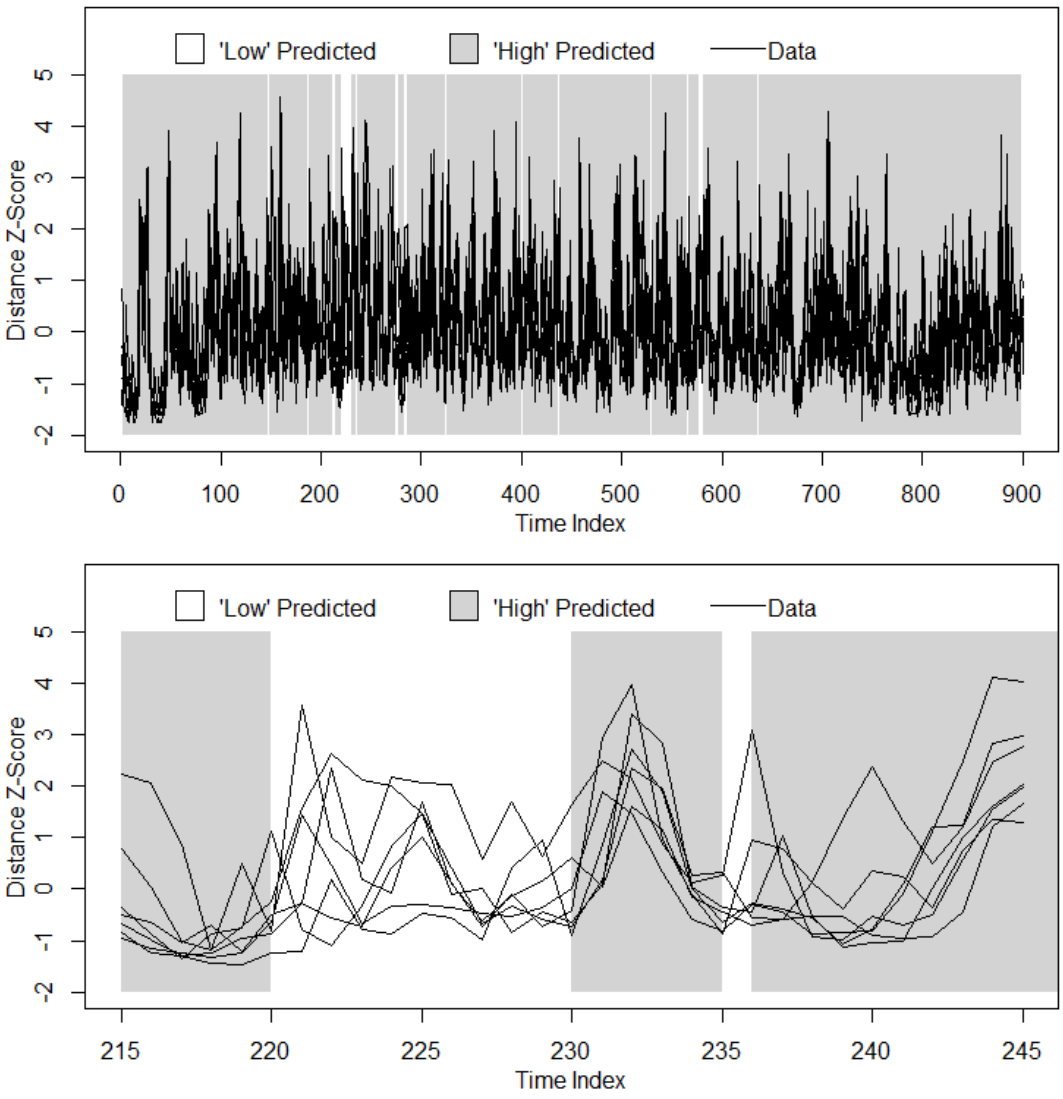

Figure 4: Study 1 Game 12 distance data superimposed on predicted regimes; full time series (top panel) and zoomed in (bottom panel).

for Regime 1 are approximately centered on zero, and the distributions for Regime 2 are approximately centered on .5, with only positive values.

The purpose of Figure 6 is to examine whether a trend emerged over the course of the season in terms of the prevalence of collective synchrony (i.e., in the Regime 2 dwell time proportions for selected RSDFMs only). For the distance analyses, there appears to be an initial increase in dwell time over roughly the first half of the season. However, it would be advisable not to read too much into this trend, due to the fact that Regime 2 was overwhelmingly prevalent in all of the analyses (i.e., greater than .88 dwell time for all 23 of the selected RSDFMs). A possible explanation for the dominance of Regime 2 is addressed in the Discussion section. Figure 7 displays the magnitude of collective synchrony, summarized as the mean effect sizes, that is, the means of the squared standardized loadings for all selected models, both DFMs and RSDFMs. Here again, there appear to be no particular trends, with the mean effect sizes mostly in the .4 to .6 range throughout the season.

3.3.3 Discussion

The analysis of cadence and distance data sets from college women's soccer produced several important outcomes worthy of discussion, both at the level of specific analyses and at the aggregate level. To exemplify the substantively relevant details that can be extracted from each analysis, I presented two sets of results using the RSDFM approach (Game 7 cadence and Game 12 distance). One characteristic of a team's collective synchrony that is likely to have scientific and practical value is the magnitude of collective synchrony. In particular, standardized loadings, when squared equal the effect size, the proportion of variance in each observed time series explained by the collective state variable. This can be interpreted as the extent of each individual's synchrony with the collective. In

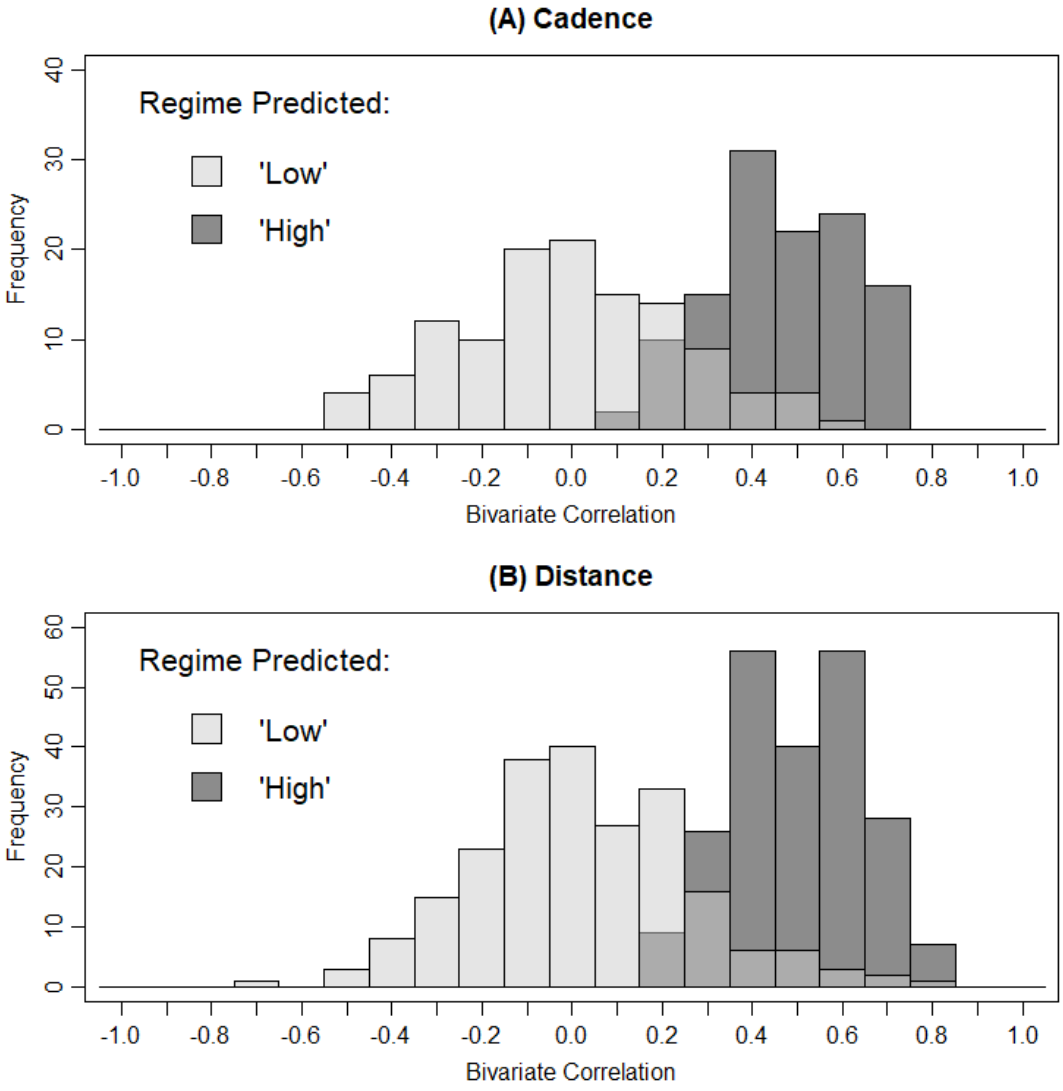

Figure 5: Overlapping histograms of bivariate correlations between all teammate pairs; low vs. high collective synchrony regimes for selected RSDFMs only (Study 1).

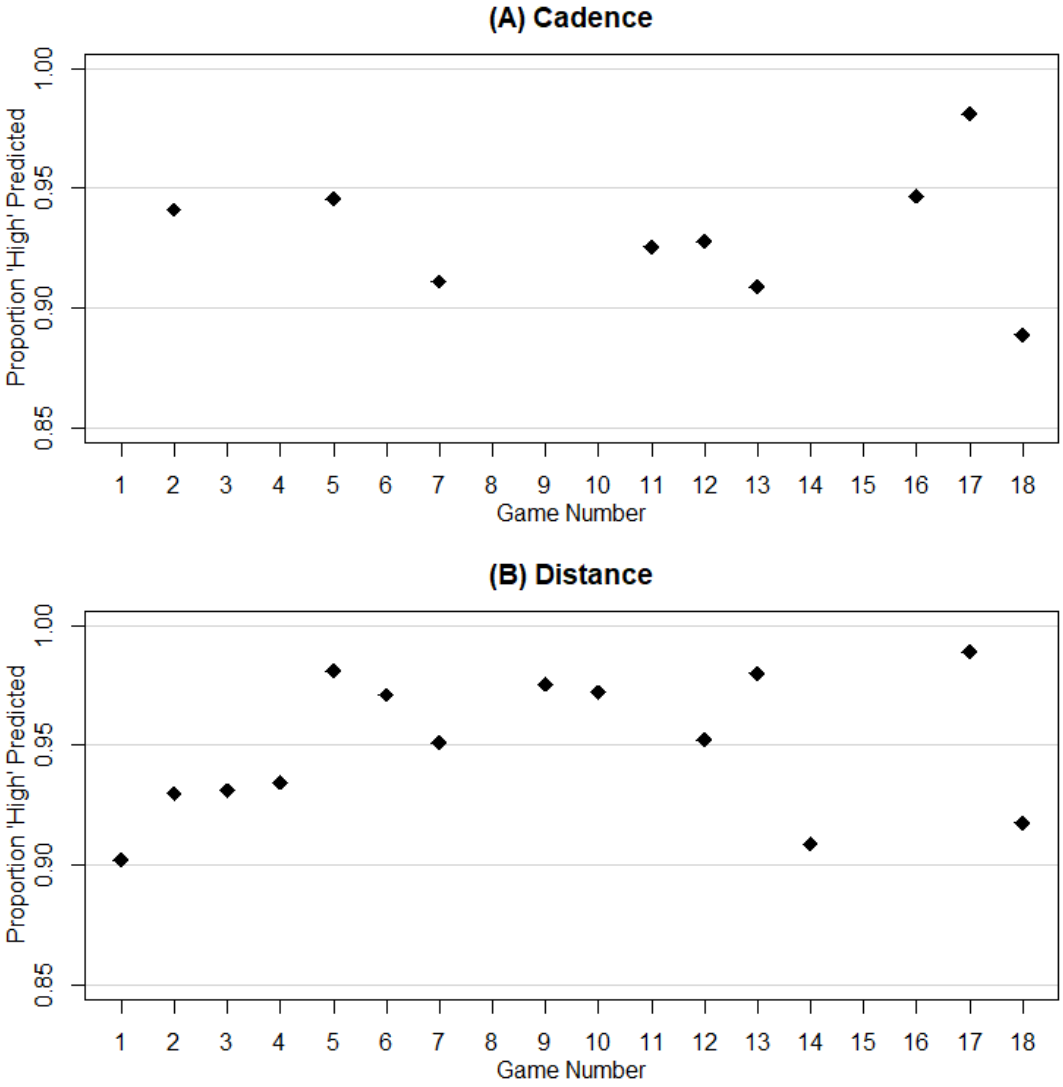

Figure 6: Proportion dwell time in high collective synchrony regime, over 18 games (Study 1).

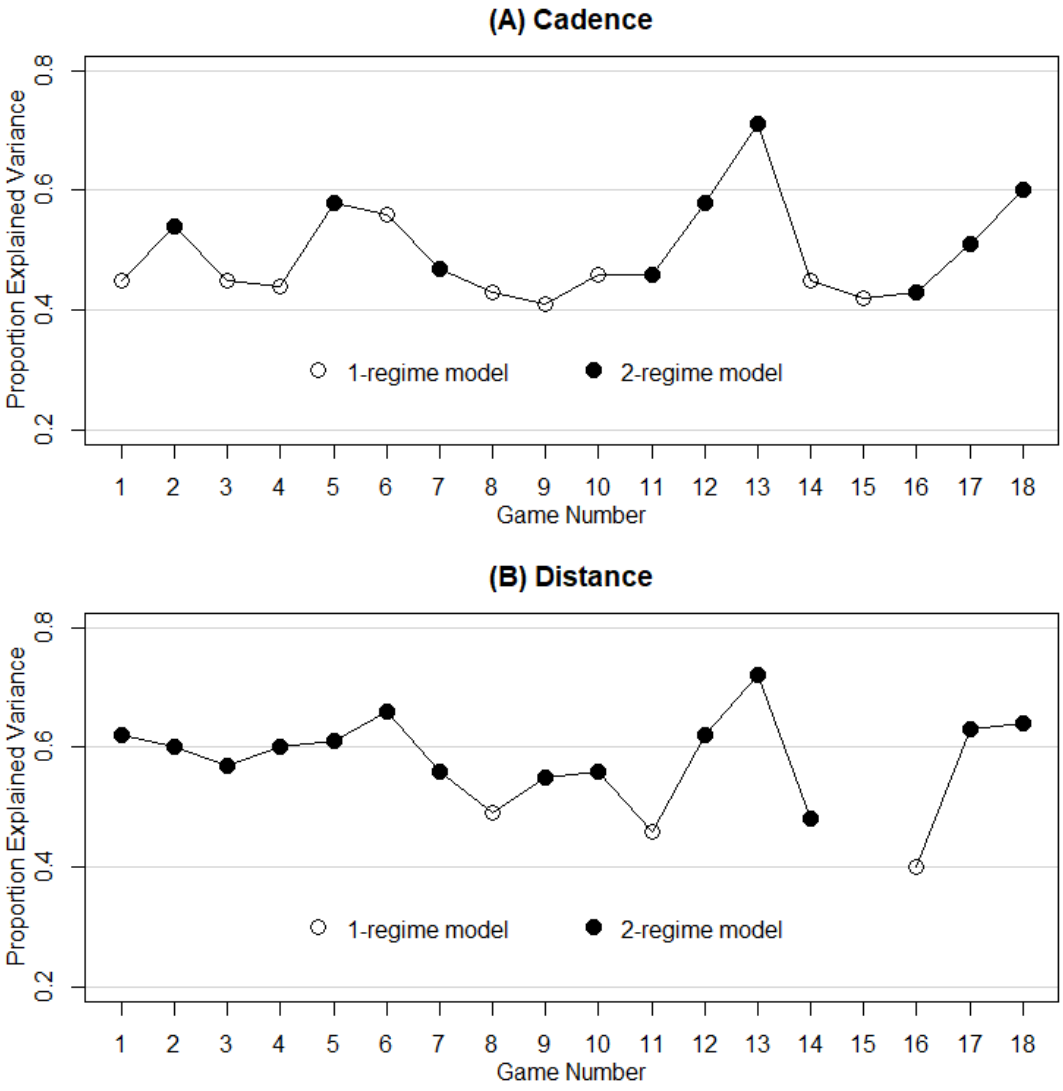

Figure 7: Mean effect sizes, over 18 games (Study 1).

the Game 7 example, it was noted that one individual's cadence (y_2) was not as well synchronized to the collective as the cadences of the other six members. The small standardized loading (.20) and small bivariate correlations between y_2 and each other time series in predicted Regime 2 supported this finding. Hence, with this analytical approach it is possible to identify individuals who contribute more or less than others to collective synchrony, which has practical value to those affiliated with teams such as coaches, performance analysts, sport psychologists, and/or the athletes themselves. Additionally, presenting specific examples made it possible to show didactically how the bivariate correlations among time series can be inspected separately for the two predicted regimes for comparison, and how the estimated regime switching probabilities (π_{ij}) and proportion of dwell time reflect the prevalence of each regime. Plotting the predicted regimes is also useful to visualize the prevalence of each regime.

Other important outcomes of Study 1 can be examined at the aggregate level. This is useful, as in the case of this study, when analyzing collective synchrony within many measurement epochs (e.g., games) spanning a longer time period (e.g., a sports season). First, to aggregate information about the magnitude of collective synchrony over all games in which a regime-switching model was selected, I generated overlapping histograms to compare the distribution of bivariate correlations in the predicted Regime 1 versus Regime 2. This confirmed what one might expect, that is, smaller correlations centered on zero in Regime 1, and larger positive correlations centered on .5 in Regime 2. Second, the mean effect sizes, computed by averaging the squared standardized loadings from each selected model, can be plotted for the 18-game season to visually assess temporal trends. This allows considering the question: does the average magnitude of a team's collective synchrony change over the course of a season? Although after visual

inspection I deemed it not worthwhile to conduct further analyses with these values (e.g., examining whether a longitudinal trend emerged over the 18-game season), it may be useful to do so in other applications. Third, I emphasized the proportion of time spent in each regime (i.e., dwell time) as a substantively valuable outcome to assess the prevalence of high collective synchrony when using RSDFMs. At the aggregate level, dwell time proportions can be plotted, for example, for all games in a season to check for changes over time.

Although no temporal pattern in dwell time was apparent in Study 1, what is clear for both of the variables analyzed is the large percentage of time spent in the high collective synchrony regime (i.e., greater than 88%). This finding is likely due to the constraints of competitive soccer. That is, particularly at the highest levels of competitive sport, the movements of teammates are often constrained to be highly similar. The observed variables cadence and distance could each be considered a sort of proxy for speed of movement. In competitive soccer, in which team members are typically arranged in and trained to maintain a particular formation, it would be expected, and beneficial to performance, for teammates to move in similar directions and at similar speeds in response to events in the game such as the position of the ball and the team in possession. Indeed, it is difficult to envision a team achieving success with some players standing still, others walking, others jogging, and others sprinting. Put another way, it would be detrimental to the team's overall performance if individuals' speeds were uncorrelated, that is, if collective synchrony was not high, for a large proportion of time points. Given the context of NCAA Division I competition, it is appropriate that the proportions of dwell time in the high collective synchrony regime were so high. In other contexts or at other levels of expertise, it may be of substantive interest to rigorously test whether a collective can show improvements over time, in terms of dwell time in a

high collective synchrony state.

3.4 Study 2: Collective Synchrony in Men's Soccer Players' Heart Rates

3.4.1 Method

Participants and Materials

Varsity men's soccer players were recruited from a NCAA Division I team in the United States. The university's Institutional Review Board approved the protocol detailing the recruitment of participants and data collection procedures for Study 2. Seven players gave informed consent to participate in the study. Six participants were randomly assigned to teams of three (Triad A and Triad B), while one participant was designated as an alternate in case of attrition due to injury or otherwise. The membership of each triad was kept the same across three separate dates of data collection, except at Session 3, when the alternate participated in place of an injured member of Triad A. The study sessions were scheduled approximately 3-5 weeks apart at team practices during the competitive 2017 season. Outfield players only (goalkeepers excluded) were recruited for Study 2. The equipment used for data collection was the same Polar® Team Pro system (Polar Electro, Inc., Kempele, Finland) used in Study 1. The men participating in Study 2 had not been previously trained on how to properly wear the chest strap monitor, so this was demonstrated at Session 1 and reviewed at Sessions 2 and 3. Data were passively recorded during each session and available for download afterward.

Design and Procedure

This study has a repeated measures design, and two experimental conditions were tested at each of the three study sessions. Each trial consisted of a 6-minute small-sided training game in which one triad's objective was to keep possession of the ball for as long as possible within a confined space (known as "keep away")

from one defender (3v1) or two defenders (3v2). Triads A and B were each tested as the team in possession twice per study session, once in a 3v1 game (low time pressure condition) and once in a 3v2 game (high time pressure condition). While a triad was being tested (i.e., was the team in possession), defenders were drawn from the other triad. Defenders were rotated into the game in regular intervals, every minute in 3v1 games and every 2 minutes in 3v2 games. When the ball went out of play or was taken by a defender, a coach immediately rolled a new ball to the triad for play to resume. The chronological order of the small-sided games is listed below. The 3v1 games preceded 3v2 games at each session, and the order of Triad A or Triad B starting in possession was alternated as much as possible, given only three sessions.

- Session 1
  - AvB (3v1)
  - BvA (3v1)
  - AvB (3v2)
  - BvA (3v2)
- Session 2
  - BvA (3v1)
  - AvB (3v1)
  - BvA (3v2)
  - AvB (3v2)
- Session 3
  - BvA (3v1)
  - AvB (3v1)
  - AvB (3v2)
  - BvA (3v2)

Time markers were entered using the Polar® system's tablet computer application to mark the start and end of each trial. The wearable devices were numbered and records were kept to ensure that data were accurately attributed to participants and triads. The identities of the individual participants were maintained for each triad over the course of the study (y_1, y_2, y_3 in Triad A; y_4, y_5, y_6 in Triad B) except for one substitution for an injured participant (y_2) in Session 3. In this study, the variable of interest is heart rate. Data sets were downloaded following each session, then processed and analyzed as detailed next.

Data Processing and Analysis

Heart rates were recorded at a rate of 1 Hz in units of beats per minute (bpm). To remedy nonstationarity due to repetitive values, data were downsampled to .5 Hz and differences between adjacent observations were computed to obtain the change in heart rate over each 2-second interval. Using a 2-second interval for heart rate has also been cited as a common and appropriate interval length in the developmental psychophysiology literature [32]. Additionally, I truncated each time series to discard the first minute of every 6-minute game. My rationale for doing so was to eliminate the initial steep incline in players' heart rates as their bodies acclimated to the physical demands of the task. The resulting time series were each approximately 150 observations in length, representing 5 minutes of activity. Each time series was standardized (converted to z-scores) prior to analysis.

As in Study 1, data streams were examined for order of ARMA process using ACF and PACF plots and by running univariate ARMA models. Most of the individual time series exhibited ACFs and PACFs similar to those illustrated in Figure B.2 (Appendix B) with the PACF significant at the first two lags (Panels B, H, J, and L), or at the second lag only (Panels D and F). Again, it was these checks that informed the use of AR(1) and AR(2) models in this study.

Out of the 12 data sets from small-sided games, five had problems with a participant's time series exhibiting large numbers of missing values and/or outliers. These problems were attributed to issues with the device, such as not achieving good contact between the sensors and skin. As a result, these data sets were discarded, and only the 7 data sets from the whole collective (triad) were used. The small-sided games used in the analysis are numbered as follows:

1. Triad A 3v1, Session 1

	1. Av1 (1)		**2. Av2 (1)**		**3. Av1 (3)**		**4. Bv1 (1)**	
	y_1	y_2	y_1	y_2	y_1	y_2	y_1	y_2
y_2	.26		.03		.20		.46	
y_3	.23	.30	.04	.13	.15	.28	.30	.49
	5. Bv1 (2)		**6. Bv2 (2)**		**7. Bv2 (3)**			
	y_1	y_2	y_1	y_2	y_1	y_2		
y_2	.12		.17		.16			
y_3	.23	.14	.09	.00	.14	.17		

Table 5: Correlations in change in heart rate data, for all 7 games in Study 2.

2. Triad A 3v2, Session 1

3. Triad A 3v1, Session 3

4. Triad B 3v1, Session 1

5. Triad B 3v1, Session 2

6. Triad B 3v2, Session 2

7. Triad B 3v2, Session 3

The **dynr** R package [29] was used for all analyses. AIC and BIC values were used to select one best fitting model for each small-sided game. Here, I used the same four models that I ran in Study 1 (i.e., AR(1) DFM, AR(2) DFM, AR(1) RSDFM, and AR(2) RSDFM). Nearly all of the regime-switching models, except for the AR(2) RSDFM from Game 4, either did not converge or had non-positive definite Hessian matrices resulting in untrustworthy standard errors. These models were discarded and not considered for selection.

In Table 5, it is apparent that the bivariate correlations in each data set were generally small by comparison to the coefficients computed in Study 1. After an initial run of the same four models used in Study 1, the AR(1) DFM (one-regime

model) was selected for all but Game 4. The fact that bivariate correlations are greater in Game 4 may explain why a regime-switching model was able to detect intervals of high and low collective synchrony for this data set alone. Given the overall smaller bivariate correlations in the heart rate data, another one-regime model was formulated and run on each data set. Whereas the DFM was intended to model the multiple time series as being driven by a common latent factor (i.e., high collective synchrony only), this model accounts for the possibility that teammates' changes in heart rates may be characterized by low collective synchrony for the game's duration. Hence the following vector autoregressive first-order, or VAR(1) model, which assumes no associations among the multiple time series, was applied:

$$\begin{bmatrix} y_{1t} \\ y_{2t} \\ y_{3t} \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} y^{\star}_{1t} \\ y^{\star}_{2t} \\ y^{\star}_{3t} \end{bmatrix} \tag{16}$$

$$\begin{bmatrix} y^{\star}_{1t} \\ y^{\star}_{2t} \\ y^{\star}_{3t} \end{bmatrix} = \begin{bmatrix} \phi_1 & 0 & 0 \\ 0 & \phi_2 & 0 \\ 0 & 0 & \phi_3 \end{bmatrix} \begin{bmatrix} y^{\star}_{1,t-1} \\ y^{\star}_{2,t-1} \\ y^{\star}_{3,t-1} \end{bmatrix} + \begin{bmatrix} \zeta_{1t} \\ \zeta_{2t} \\ \zeta_{3t} \end{bmatrix}, \quad \Psi = \begin{bmatrix} \psi_1 & 0 & 0 \\ 0 & \psi_2 & 0 \\ 0 & 0 & \psi_3 \end{bmatrix} \tag{17}$$

where each $y^{\star}$ is a state variable that simply acts as a proxy of the observation itself; each ϕ is a person-specific AR1 coefficient; and each ψ is a person-specific error variance. VAR(1) was the only order of process considered here, due to the fact that AR(1) DFMs were selected over all AR(2) DFMs run prior to the introduction of this model. AIC and BIC values were compared with other models to assess relative fit.

3.4.2 Results

AIC values and selected models are indicated in Table B.3 in Appendix B. AIC and BIC were in agreement that the best fitting model was the AR(1) DFM (one-regime model), except for Game 4, where the AR(2) RSDFM produced the smallest AIC, while the AR(1) DFM produced the smallest BIC. Similar to my

Parameter	Symbol	Est.	SE	t	95% CI	p
L1 fixed (std.)	λ_1	1.00 (.69)	-	-	-	-
L2 unstd. (std.)	λ_2	1.38 (.87)	.17	8.1	(1.05, 1.71)	<.001
L3 unstd. (std.)	λ_3	1.03 (.70)	.16	6.5	(.72, 1.34)	<.001
MEV1 reg. 1	θ_{11}	1.40	.48	2.9	(.46, 2.34)	.002
MEV2 reg. 1	θ_{21}	.65	.23	2.9	(.21, 1.09)	.002
MEV3 reg. 1	θ_{31}	1.10	.47	2.3	(.17, 2.02)	.011
MEV1 reg. 2	θ_{12}	.53	.10	5.4	(.34, .72)	<.001
MEV2 reg. 2	θ_{22}	.24	.07	3.6	(.11, .37)	<.001
MEV3 reg. 2	θ_{32}	.51	.08	6.6	(.36, .66)	<.001
AR1 coefficient	ϕ_1	.43	.13	3.2	(.17, .69)	.001
AR2 coefficient	ϕ_2	.53	.13	4.0	(.28, .79)	<.001
IE var.	ψ	.12	.03	3.3	(.05, .18)	.001
Log odds 1→1	$\ln(\frac{\pi_{11}}{1-\pi_{11}})$	1.26	.71	1.8	(-.12, 2.65)	.038
Log odds 2→1	$\ln(\frac{\pi_{21}}{1-\pi_{21}})$	-3.20	.73	-4.4	(-4.62, -1.77)	<.001

Note: CI = confidence interval; Est. = estimate; IE = innovation error; L = loading; MEV = measurement error variance; p = p-value; reg. = regime; SE = standard error; std. = standardized; t = Student's t test statistic; unstd. = unstandardized; var. = variance

Table 6: Parameter estimates from AR(2) RSDFM fit to Game 4 change in heart rate data in Study 2.

presentation of Study 1 results, here I show two specific examples of analyses before summarizing results at the aggregate level. The two examples include Game 4 (RSDFM results) and Game 6 (AR(1) DFM and VAR(1) results).

Parameter estimates from the Game 4 AR(2) RSDFM can be found in Table 6. The effect sizes, or proportions of variance in y_1, y_2, and y_3 explained by the latent collective variable, are .47, .76, and .49, respectively. The bivariate correlations in analyzed time series within predicted low synchrony intervals were -.07, -.45, and -.17, compared to .58, .48, and .60 within predicted high synchrony intervals (i.e., for y_1-y_2, y_1-y_3, and y_2-y_3, respectively). The prevalence of Regime 2 is apparent in its proportion dwell time of .83 (i.e., 125 out of 150 time points as shown in the top panel of Figure 8) and in the disparate estimated regime transition probabilities ($\pi_{11} = .779$, $\pi_{22} = .959$). The bottom panel of Figure 8 is zoomed in on 30 time points to show what the data look like in one predicted regime or the other.

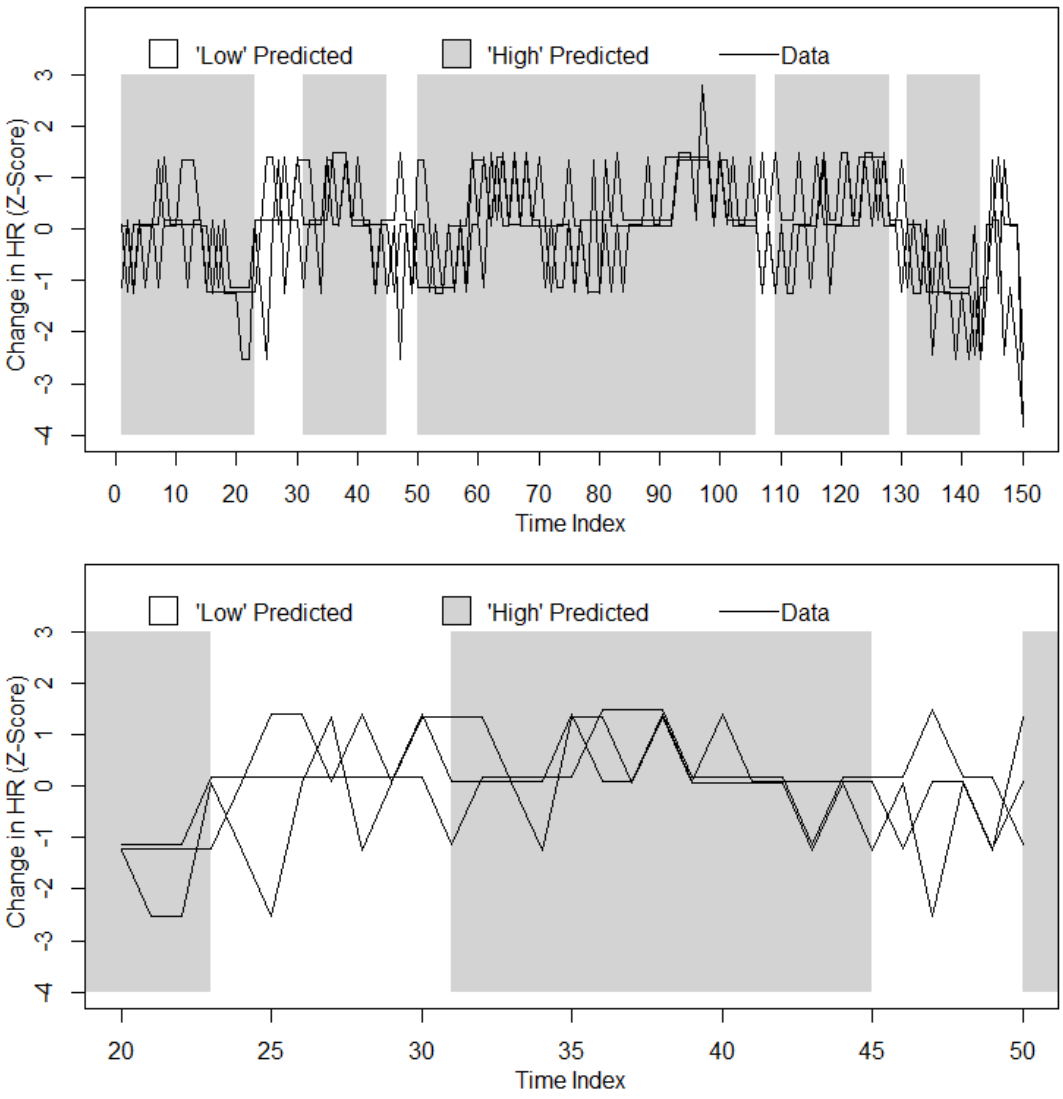

Figure 8: Study 2 Game 4 change in heart rate data superimposed on predicted regimes; full time series (top panel) and zoomed in (bottom panel).

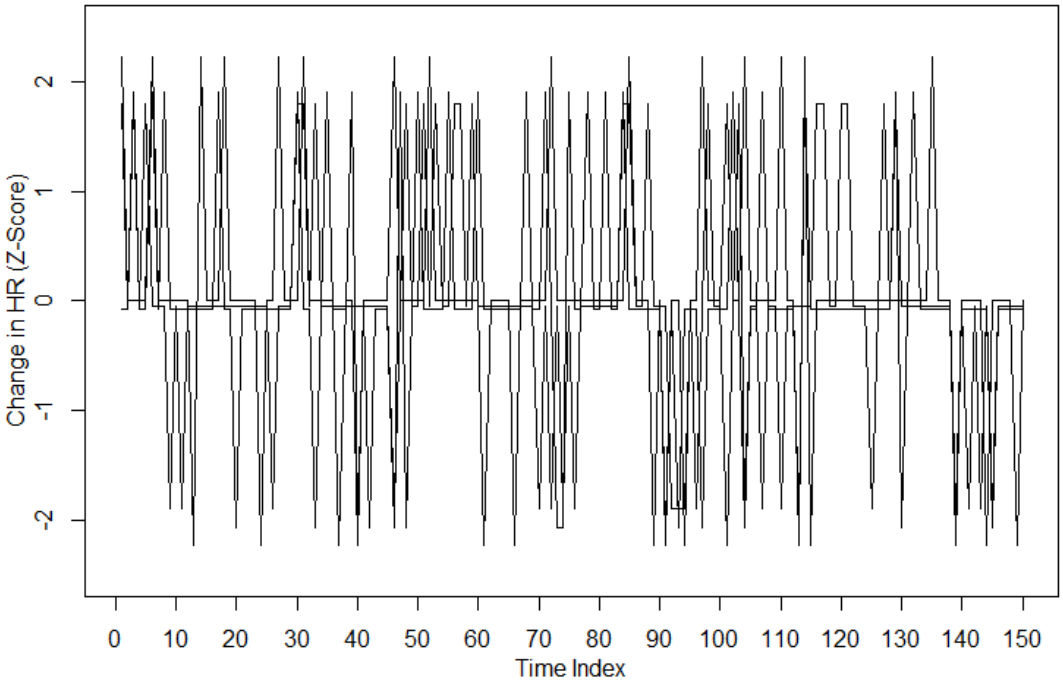

Figure 9: Study 2 Game 6 change in heart rate data.

Next, results from the analysis of Game 6 data are presented. Change in heart rate time series from Triad B in Game 6 are plotted in Figure 9. Parameter estimates from this analysis can be found in Table 7. In Panel a, results of the selected model, AR(1) DFM, are presented. Owing to the overall low collective synchrony in players' changes in heart rate in Game 6, the estimated measurement error variances are high, in particular for persons 1 and 3, for the AR(1) DFM (consistent with low bivariate correlations in Table 5). For illustration, in Panel b of Table 7, I present the results of the VAR(1) model fit to the Game 6 data. The error variance (ψ_i) estimates, standard errors, and confidence intervals shown in Panel b are comparable to those of θ_1 and θ_3 shown in Panel a. However, the estimate for θ_2 reflects 71% unexplained variance in y_2. These results suggest that the AR(1) DFM was deemed a better fitting model than the VAR(1) presumably due to the 29% of variance in y_2 explained by the latent collective variable incorporated in

Parameter	Symbol	Est.	SE	t	95% CI	p
L1 fixed (std.)	λ_1	1.00 (.22)	-	-	-	-
L2 unstd. (std.)	λ_2	2.15 (.54)	.92	2.3	(.35, 3.95)	.010
L3 unstd. (std.)	λ_3	.68 (.20)	.46	1.5	(-.22, 1.59)	.070
MEV1	θ_1	.95	.11	8.6	(.73, 1.16)	<.001
MEV2	θ_2	.71	.13	5.6	(.46, .96)	<.001
MEV3	θ_3	.96	.12	8.3	(.74, 1.19)	<.001
AR1 coef.	ϕ_1	.73	.10	7.2	(.53, .93)	<.001
IE var.	ψ	.02	.02	1.3	(-.01, .06)	.104

(a) AR(1) DFM results (AIC = 1277)

Parameter	Symbol	Est.	SE	t	95% CI	p
AR1 coef. person 1	ϕ_1	-.14	.08	-1.7	(-.30, .02)	.045
AR1 coef. person 2	ϕ_2	.13	.08	1.7	(-.02, .29)	.048
AR1 coef. person 3	ϕ_3	-.10	.08	-1.2	(-.26, .06)	.107
Error var. person 1	ψ_1	.98	.11	8.6	(.76, 1.20)	<.001
Error var. person 2	ψ_2	.96	.11	8.6	(.74, 1.18)	<.001
Error var. person 3	ψ_3	.96	.11	8.6	(.74, 1.17)	<.001

(b) VAR(1) results (AIC = 1291)

Note: CI = confidence interval; coef. = coefficient; Est. = estimate; IE = innovation error; L = loading; MEV = measurement error variance; p = p-value; SE = standard error; std. = standardized; t = Student's t test statistic; unstd. = unstandardized; var. = variance

Table 7: Parameter estimates from models fit to Game 6 change in heart rate data in Study 2.

the DFM. This perhaps gives a hint as to why the VAR(1) model was not selected (did not have the lowest AIC/BIC) for any of the seven data sets. I expand on this point further in the Discussion. Next, Study 2 results are presented in aggregate.

Figure 10 shows, for the selected model from each game in Study 2, the mean effect sizes, that is, the mean proportion of variance in the observed variables explained by the collective state variable. For DFMs and RSDFMs, this provides a metric of the magnitude of collective synchrony in the time series. The Game 4 data set (Triad B 3v1, Session 1), which was the only one for which a regime-

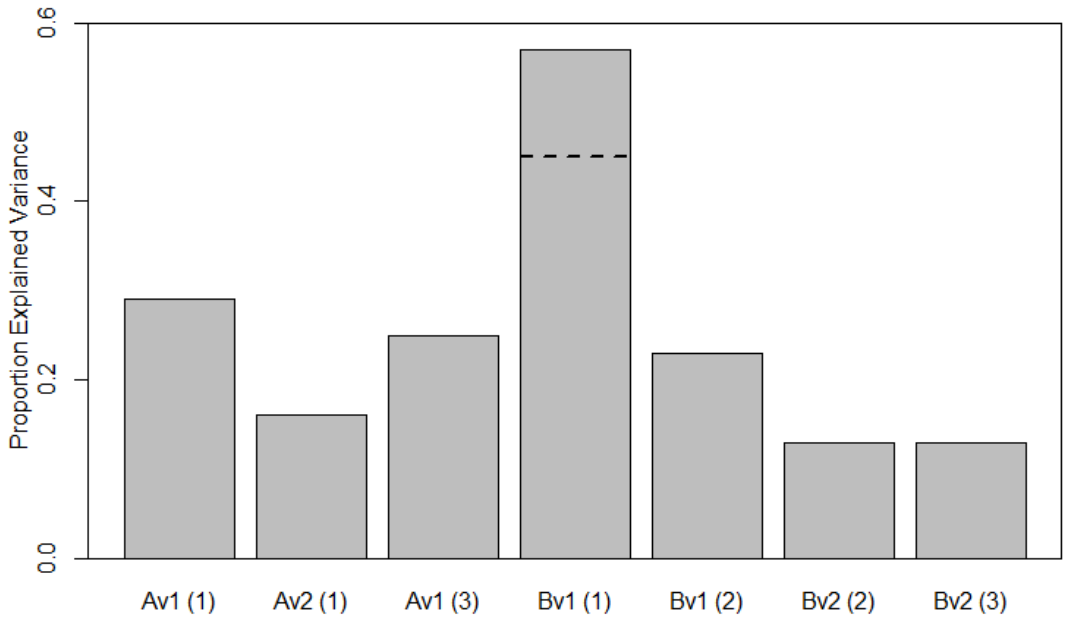

Figure 10: Mean effect sizes in each of 7 games (Study 2); dashed line represents the AR(1) DFM for Game 4.

switching model was selected, clearly exhibits the greatest magnitude of collective synchrony. RSDFMs tend to exhibit greater explained variance in Regime 2, in comparison to one-regime DFMs. For this reason (i.e., to compare "like with like"), the mean explained variance for the Game 4 AR(1) DFM, which was the preferred model for all other data sets, is indicated with a dashed line at .45 in Figure 10. This value still far exceeds the others and is consistent with the relatively larger correlation coefficients computed for this data set (see Table 5). Moreover, there appears to be a tendency for the data sets from high time pressure (3v2) games (i.e., Games 2, 6, and 7) to produce smaller values of explained variance than data sets from low time pressure (3v1) games. Possible explanations for this are offered in the Discussion section next.

3.4.3 Discussion

In this study, collective synchrony was examined in NCAA men's soccer players' change in heart rate during 3v1 and 3v2 practice games. Study 2 offers a number of interesting, novel methodological findings. The results from Game 4, involving Triad B playing 3v1 at the first study session, demonstrate one example in which the magnitude of collective synchrony in heart rate changes was high by comparison to other games in Study 2. Referring to Manuscript 1 of this dissertation, one could cite the teammates' shared cognitive, emotional, and behavioral experiences as possible explanations of heightened collective synchrony in their heart rate changes. However, it is unclear why this would be true of this particular game but not, for example, of Game 5, which was Triad B's 3v1 game in Session 2, played several weeks later. That disparity in and of itself is interesting as it suggests that there was possibly an influential third variable differentiating Games 4 and 5.

The fact that the RSDFM was useful for modeling the Game 4 data, but not other data sets in Study 2, points to the possibility that, when there is a greater overall magnitude of collective synchrony (i.e., greater correlation and greater variance explained by the collective state variable), an RSDFM seems to be better able to detect when periods of low or zero collective synchrony occur. In other words, it is easier to categorize periods of high and low collective synchrony as two distinct regimes. Intuitively, this makes sense that it would be more challenging to distinguish between regimes when the magnitude of collective synchrony is small overall (i.e., low vs. lower or none), which was the case in most of the data sets in Study 2. Under these conditions, a one-regime model seems to perform better.

In this study, I introduced a one-regime VAR(1) model intended to mimic Regime 1 of the RSDFM, as a counterpart to one-regime DFMs, which reflect

Regime 2 of the RSDFM. In all of the data sets analyzed, DFMs were selected over VAR models. This suggests that a one-regime model accounting for collective synchrony (i.e., DFM) fits better than a one-regime model assuming the individual time series to be uncorrelated (i.e., VAR), even when the magnitude of collective synchrony is quite low. For Game 6, which involved Triad B playing 3v2 at the second study session, the results from both the AR(1) DFM as the selected model and the VAR(1) for illustration and comparison were reported. There, I noted that the 29% explained variance in y_2, and in the same vein a significant estimate for λ_2, was likely why the DFM was deemed a better fitting model than the VAR model.

Another interesting outcome of Study 2 was the apparent tendency for 3v2 games to produce lower collective synchrony in heart rate changes than 3v1 games. This trend can be inspected in Figure 10 (i.e., mean effect sizes lower for 3v2 games compared to 3v1 games), and is also reflected in the smaller bivariate correlations for Games 2, 6, and 7 listed in Table 5. Although this conclusion is based on visual inspection and not tested rigorously, it is valuable to discuss possible reasons why collective synchrony might be of a lower magnitude under conditions of high time pressure (3v2) compared to low time pressure (3v1). This may be a consequence of elevated physical exertion required during the 3v2 task, which produces higher and, crucially, less varied heart rates. Specifically, participants' overall mean (and standard deviation) heart rate in the 3v2 condition was 182 (8.4) bpm, compared to 173 (10.9) bpm in the 3v1 condition. The limited variability in heart rate from time point to time point, spaced 2 seconds apart, is evident in the raw difference data. The relative frequency tables of these data are compared for the 3v1 and 3v2 conditions in Table 8. Here it is clear that the proportion of zeros is higher, and the proportion of nonzero values lower, in the 3v2 condition. The relatively

	-3	-2	-1	0	1	2
3v1	<.01	.01	.18	.61	.19	<.01
3v2			.11	.72	.16	<.01

Table 8: Relative frequencies of raw changes in heart rate, by condition.

limited changes in heart rate make it inherently less likely that there would be strong correlations between teammates' time series.

The following are limitations of Study 2. First, heart rates were recorded by the Polar® devices as integer values. As a consequence, changes between them were also integers, primarily -1, 0, and 1, with a large proportion of zeros. This lack of continuous data and the limited changes in heart rate were unfavorable for examining collective synchrony among multiple time series. This likely contributed to the low magnitude of collective synchrony reported in this study, especially in 3v2 data. Second, instrumentation issues led to discarding five out of the 12 data sets that had been collected. As a result, it was not possible to explore certain comparisons such as within-triad changes in collective synchrony across multiple study sessions, within-triad differences comparing the 3v1 and 3v2 conditions, and between-triad differences. Third, the scope of Study 2 was small in terms of the number of triads and time points, and the fact that Triad A played with a substitute participant in Session 3 due to an injury. This exacerbated the difficulties with making within- and between-triad comparisons that may have been substantively valuable. However, several findings unique to Study 2 are highly valuable from a methodological standpoint.

3.5 Conclusion

This paper featured didactic presentation of a regime-switching dynamic factor analytic approach and two empirical studies. This inquiry produced several important developments in the study of collective synchrony. First, unlike most

other synchrony applications, which tend to focus on dyads, here I have employed a multivariate approach to enable the examination of synchrony in groups of three or more (i.e., collective synchrony). Studies 1 and 2 incorporated teams of various sizes ranging from three to nine. Second, as opposed to studies that have used metrics to quantify synchrony over the duration of a time interval as a single aggregate value, I used a regime-switching approach to account for temporal changes between states of high and low collective synchrony. Third, the dynamic factor modeling approach used in these studies enabled the weighting of each individual player's unique influence on the synchrony of the collective. These weights, or factor loadings, can be squared to obtain effect sizes (i.e., proportions of explained variance), which quantify the magnitude of collective synchrony. These can be examined on an individual basis and summarized for all team members by computing the mean of their values, for example. Fourth, by categorizing time intervals as residing within either a high or low collective synchrony regime, this modeling approach allows the researcher to extract information about the prevalence of collective synchrony. That is, what proportion of time (i.e., dwell time) is spent in the high collective synchrony regime over a given time interval analyzed? I have shown how these features, magnitude and prevalence, can be aggregated and depicted graphically in order to summarize multiple epochs of observation over a longer time period.

In terms of the methodological aim, this series of investigations has been largely a success at demonstrating the value of the RSDFM approach to analyzing collective synchrony. In both empirical studies, it was apparent that the parameter estimates and predicted regimes can be useful to directly interpret about a single time interval (e.g., dwell time within one game; magnitude of synchrony of one player's behavior with that of the collective), and to aggregate for a larger set

of events (e.g., many games within a season). Study 2 demonstrated that a one-regime DFM tends to be favored when collective synchrony is low overall across a multivariate (i.e., multi-person) time series.

Substantively, three findings are particularly noteworthy. First, each player's unique contribution to collective synchrony can be detected in the form of a standardized factor loading. The practical significance of this cannot be overstated. This implies that stakeholders interested in team performance (e.g., coaches, analysts, players, support staff) could use this information to identify and address possible weaknesses in terms of collective synchrony. Second, the large dwell time proportions of the high collective synchrony regime observed in college women's soccer players' running cadences and distances is notable. In earlier text, I suggested that this is likely due to the task constraints of high-level competitive soccer. Third, it is interesting that the collective synchrony in men's soccer teammates' heart rates was overall low, except in one game.

The above methodological and substantive findings are salient in the fledgling science of collective synchrony, and they point to multiple avenues for future work. Regarding the methodological approach, first, simulation studies are needed to systematically evaluate the RSDFM approach under varying conditions such as number of persons, number of time points, frequency of regime switching, and other model parameters. Second, more application is needed with multivariate time series exhibiting greater balance between high and low collective synchrony, unlike in Study 1 where the high collective synchrony regime dominated. Third, it would be worthwhile to assess the value of approaching the regime-switching framework as a continuous time model [33]. This may be particularly advantageous when observations are not equally spaced and/or when individuals within a collective are observed over the same time period but not at the exact same time points. Fourth,

multifactor models may be useful to assess whether there are "sub-collectives" within a team. In other words, are there subgroups within a team that demonstrate collective synchrony such as attackers/defenders or left/central/right positions? Fifth, beyond *magnitude* and *prevalence*, which I highlighted as two important features of collective synchrony, it may be worthwhile to explore the *stability* of collective synchrony. That is, for what duration does a team typically reside in one regime before switching to the other? Finally, from a methods perspective, one of the outcomes of Study 2 raises the question of whether a RSDFM can be formulated to effectively detect more subtle regime changes (e.g., low collective synchrony vs. none). It may be advantageous to establish guidelines for determining absolute cutoffs to differentiate between low synchrony and no synchrony. In this paper, I have used effect size (explained variance) and correlation to quantify the magnitude of collective synchrony. Leveraging null hypothesis significance testing (i.e., p-values and confidence intervals) is a possibility for establishing a cutoff between low and no synchrony. For example, one possibility is to create pseudo-collectives by randomly drawing time series from different games, then computing confidence intervals of correlations among these unrelated time series, in order to characterize a state of no collective synchrony.

There are numerous possible substantive directions for future research. More studies are needed to understand the relationship between team performance and collective physiological synchrony, for example. This has been the focus of a few studies [34, 35, 36], but this relationship is still not well understood. As it was suggested in the Introduction of this paper, an important future direction will be to control for copresence, characteristics of the shared task, and/or coordination, in order to tease out the effect of each on collective behavioral and physiological synchrony. Understanding the unique role of each antecedent in the context of

team performance would have tremendous scientific and practical importance. For example, to what extent is collective synchrony in physiology related to interindividual matching of emotion, and not simply a byproduct of the metabolic demands of physical exertion? It would also be useful to investigate collective synchrony in other variables not included in this paper such as players' direction of movement (i.e., change in longitudinal and lateral position). Another critical question that remains is whether collective synchrony in a given variable can be developed within a team. That is, can a team gain expertise in collective synchrony? If so, a subsequent aim would be to identify whether and how it is possible to train collective synchrony. Finally, another important remaining issue for future research is to clarify what specifically is the relationship between collective synchrony and collective flow. If collective flow is an outcome of collective synchrony as I have rendered in Manuscript 1 of this dissertation (Figure 1), then it is plausible that regime changes in collective synchrony may reflect the emergence/departure of collective flow states. Although there is still much to uncover about how collective synchrony manifests during team sports performance, this paper has taken some very important steps to establish a framework for scholarly inquiry in the field.

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APPENDIX A

Applied Simulation Study

A.1 Overview and Method

To test the regime-switching dynamic factor model (RSDFM), I simulated multivariate time series of known regimes. That is, I generated time series to show a high degree of collective synchrony within certain predetermined intervals, and lack collective synchrony otherwise. The simulated data sets were intended to have characteristics similar to the movement data collected from women's soccer players for Study 1, and the heart rate data collected from men's soccer players for Study 2. Characteristics of these test data sets are listed in Table A.1. Each univariate time series was simulated in R [1] using the `arima.sim` function by allowing the AR coefficient(s) to be randomly sampled from a uniform distribution bounded at the values shown in Table A.1. The R code used in this simulation is provided at the end of this appendix. To ensure representativeness of the empircal data, the ranges of AR1 and AR2 coefficient values were selected based on what was typical of the data collected for Studies 1 and 2. This was assessed by inspecting the partial autocorrelation function (PACF) plots of individual observed time series (see Figures B.1 and B.2 in Appendix B). That is, although an AR(2) generating function was used in this simulation, the Study 1 test data was simulated such that the AR2 coefficient was negative but for some individual time series may have been close enough to zero to be non-significant (effectively, an AR(1) process, as was characteristic of some of the observed time series). Similarly, the Study 2 test data was simulated such that the AR1 coefficient was positive but possibly non-significant for some individual time series (again, consistent with the observed time series).

Following the initial generation of time series, the virtual collective lacked

	Study 1	Study 2
Number of persons (p)	6	3
Number of time points (T)	900	150
Length of regime intervals	90	25
Range of AR1 coefficient	(.50, .70)	(.00, .40)
Range of AR2 coefficient	(-.20, .00)	(.20, .40)

Table A.1: Characteristics of simulated test data sets intended to reflect empirical data from Study 1 and Study 2.

any synchrony, that is, the time series were uncorrelated. Synchrony was then introduced in certain intervals by adding a collective process, a set of randomly sampled values that would cause each time series to increase or decrease uniformly. Finally, each time series was standardized, that is, converted to z-scores. Standardizing the data allows each measurement error variance to be easily interpreted as the proportion of variance not explained by the latent collective variable.

As shown in Tables A.2 and A.3, bivariate correlations in the time series were smaller in the simulated "low" synchrony intervals (Panel a), larger in the "high" synchrony intervals (Panel b), and moderate overall (Panel c). A subset of the simulated data intended to parallel that of Study 1 is shown in Figure A.1 where the collective behavior of the time series is apparent in the first 90 time points, but subsequently the time series appear to scatter randomly and adhere to no particular pattern. The R package **dynr** [2] was used to fit the RSDFM to the data. For each test data set, both AR(1) and AR(2) models were used. The better fitting model was selected by comparing Akaike Information Criterion (AIC) [3] and Bayesian Information Criterion (BIC) [4] fit indices for each model. When comparing AIC and BIC, smaller values indicate better model fit. Estimated parameters include the factor loadings for Regime 2 ($\lambda_2, \ldots, \lambda_p$), measurement error variances for each regime ($\theta_{11}, \ldots, \theta_{p1}, \theta_{12}, \ldots, \theta_{p2}$), one or two autoregression coefficients for

	y_1	y_2	y_3	y_4	y_5
y_2	-.02				
y_3	-.09	.01			
y_4	-.08	.01	.03		
y_5	.04	.06	.02	.02	
y_6	-.08	-.02	.03	.04	-.01

(a) "Low" synchrony intervals

	y_1	y_2	y_3	y_4	y_5
y_2	.53				
y_3	.51	.53			
y_4	.49	.56	.55		
y_5	.47	.48	.46	.40	
y_6	.40	.49	.50	.48	.37

(b) "High" synchrony intervals

	y_1	y_2	y_3	y_4	y_5
y_2	.25				
y_3	.21	.27			
y_4	.20	.28	.29		
y_5	.25	.27	.25	.21	
y_6	.15	.23	.27	.25	.19

(c) Overall

Table A.2: Correlations in simulated test data (Study 1, $p = 6$).

	y_1	y_2
y_2	.09	
y_3	.03	.00

(a) "Low" synchrony intervals

	y_1	y_2
y_2	.62	
y_3	.53	.64

(b) "High" synchrony intervals

	y_1	y_2
y_2	.38	
y_3	.31	.36

(c) Overall

Table A.3: Correlations in simulated test data (Study 2, $p = 3$).

the latent collective variable (ϕ_1, ϕ_2), the innovation error variance (ψ), and the natural log odds of the regime transition probabilities $(\ln(\frac{\pi_{ij}}{1-\pi_{ij}}))$.

A.2 Results

For both test data sets, the AR(1) model was selected over the AR(2) model based on comparisons of AIC and BIC. For the models fit to the test data emulating Study 1, the AR(1) model was selected based on both a smaller AIC value (14491, compared to 14493) and a smaller BIC value (14592, compared to 14598). For the models fit to the Study 2 test data, the AIC values were approximately equal (both 1242), but a smaller BIC value favored the AR(1) model (1278 vs. 1281). Figures A.2 and A.3 illustrate each simulated data set superimposed on the predicted and actual regimes. The plot regions indicated by dashed lines denote the actual high synchrony regime. The shaded regions denote time intervals categorized by the

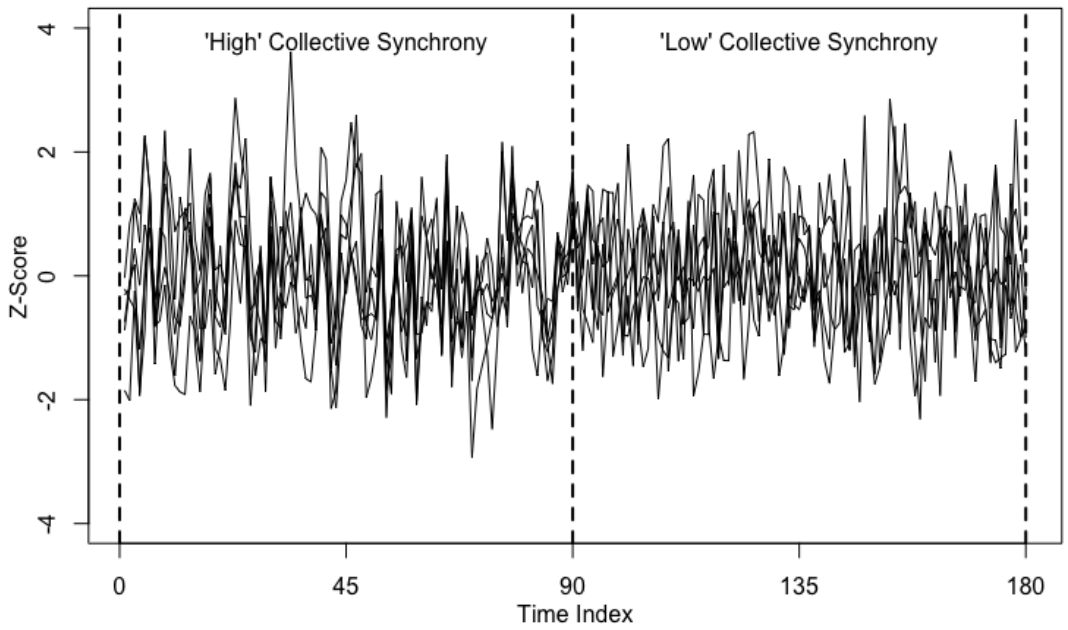

Figure A.1: First 180 time points of simulated test data illustrating "high" and "low" collective synchrony regimes (Study 1, $p = 6$).

model as the high synchrony regime, whereas the white background reflects the low synchrony regime as predicted by the model. In Figure A.2 it is clear that the model performed very well at categorizing the regimes accurately, as indicated by the predicted "high" regime (shaded region) coinciding almost entirely with the actual (dashed line region). However, in Figure A.3 it is apparent that the model did not perform quite as well with the second test data set. This is evident in the shaded regions falling outside of the dashed line regions (i.e., "high" regime predicted within the actual "low" regime).

Parameter estimates from RSDFMs fit to the simulated test data can be found in Tables A.4 and A.5. Having converted the data to z-scores, the estimated measurement error variances can be directly interpreted as the proportion of variance not explained by the latent collective variable. This is why all of the

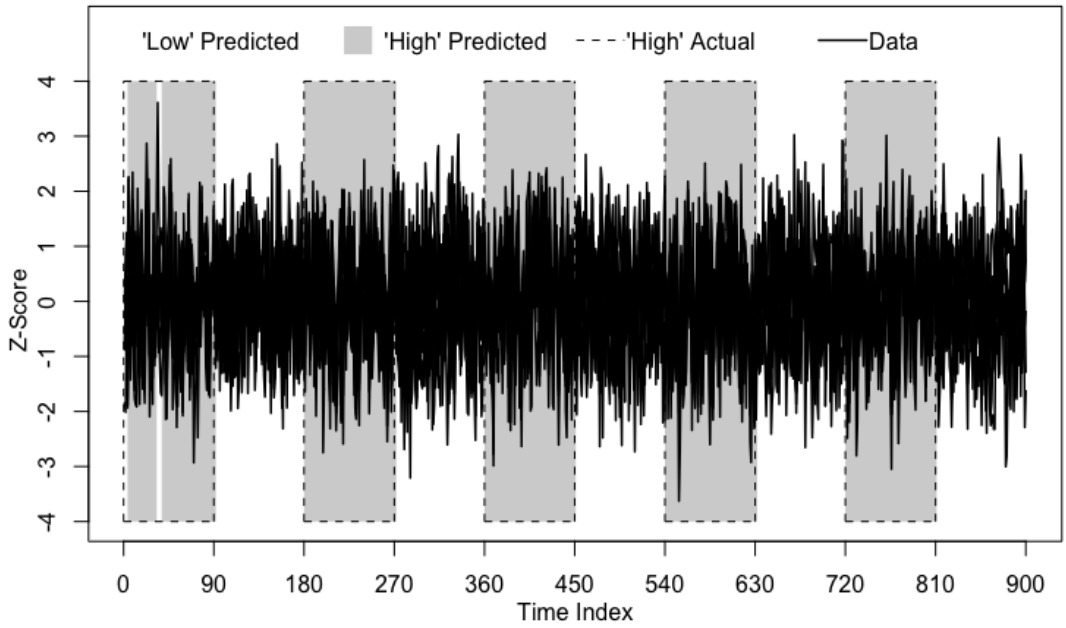

Figure A.2: Simulated test data superimposed on predicted and actual regimes (Study 1, $p = 6$).

measurement error variances estimated for Regime 1, in which the model assumes no collective process driving the observations, have confidence intervals spanning 1 (i.e., 100% unexplained variance). The smaller estimates for the measurement error variances in Regime 2 reflect that some proportion of the variance is explained by the collective state variable (C_t). Conversely, the standardized loadings, shown in parentheses in the "Est." column of Tables A.4 and A.5, when squared, equal the proportion of explained variance (i.e., 1 minus the Regime 2 measurement error variance; or, 1 minus the unexplained variance). For the Study 1 test data, the explained variance ranges from .35 to .58, values which are comparable to the bivariate correlations among the time series in Regime 2; see Table A.2(b). In the same vein, for the Study 2 test data, the explained variance ranges from .42 to .60, similar to the correlations in Panel b of Table A.3.

Parameter	Symbol	Est.	SE	t	95% CI	p
L1 fixed (std.)	λ_1	1.00 (.71)	-	-	-	-
L2 unstd. (std.)	λ_2	1.08 (.76)	.08	13.7	(.93, 1.24)	<.001
L3 unstd. (std.)	λ_3	1.10 (.73)	.08	13.6	(.94, 1.26)	<.001
L4 unstd. (std.)	λ_4	1.04 (.71)	.08	13.0	(.88, 1.19)	<.001
L5 unstd. (std.)	λ_5	.91 (.59)	.08	11.6	(.75, 1.06)	<.001
L6 unstd. (std.)	λ_6	.90 (.68)	.08	11.8	(.75, 1.05)	<.001
MEV1 reg. 1	θ_{11}	1.03	.07	14.9	(.90, 1.17)	<.001
MEV2 reg. 1	θ_{21}	1.03	.07	14.8	(.89, 1.16)	<.001
MEV3 reg. 1	θ_{31}	.96	.06	14.9	(.83, 1.08)	<.001
MEV4 reg. 1	θ_{41}	1.00	.07	14.7	(.86, 1.13)	<.001
MEV5 reg. 1	θ_{51}	.96	.06	14.8	(.83, 1.09)	<.001
MEV6 reg. 1	θ_{61}	1.07	.07	14.4	(.93, 1.22)	<.001
MEV1 reg. 2	θ_{12}	.49	.04	11.5	(.41, .57)	<.001
MEV2 reg. 2	θ_{22}	.42	.04	11.0	(.34, .49)	<.001
MEV3 reg. 2	θ_{32}	.47	.04	11.4	(.39, .55)	<.001
MEV4 reg. 2	θ_{42}	.49	.04	11.9	(.41, .57)	<.001
MEV5 reg. 2	θ_{52}	.65	.05	13.0	(.55, .74)	<.001
MEV6 reg. 2	θ_{62}	.54	.05	11.7	(.45, .63)	<.001
AR1 coefficient	ϕ_1	.03	.06	0.6	(-.08, .14)	.279
IE var.	ψ	.48	.06	7.7	(.35, .60)	<.001
Log odds 1→1	$\ln(\frac{\pi_{11}}{1-\pi_{11}})$	4.24	.44	9.5	(3.37, 5.11)	<.001
Log odds 2→1	$\ln(\frac{\pi_{21}}{1-\pi_{21}})$	-4.24	.45	-9.4	(-5.13, -3.35)	<.001

Note: CI = confidence interval; Est. = estimate; IE = innovation error; L = loading; MEV = measurement error variance; p = p-value; reg. = regime; SE = standard error; std. = standardized; t = Student's t test statistic; unstd. = unstandardized; var. = variance

Table A.4: Parameter estimates from the AR(1) RSDFM fit to simulated test data (Study 1, $p = 6$).

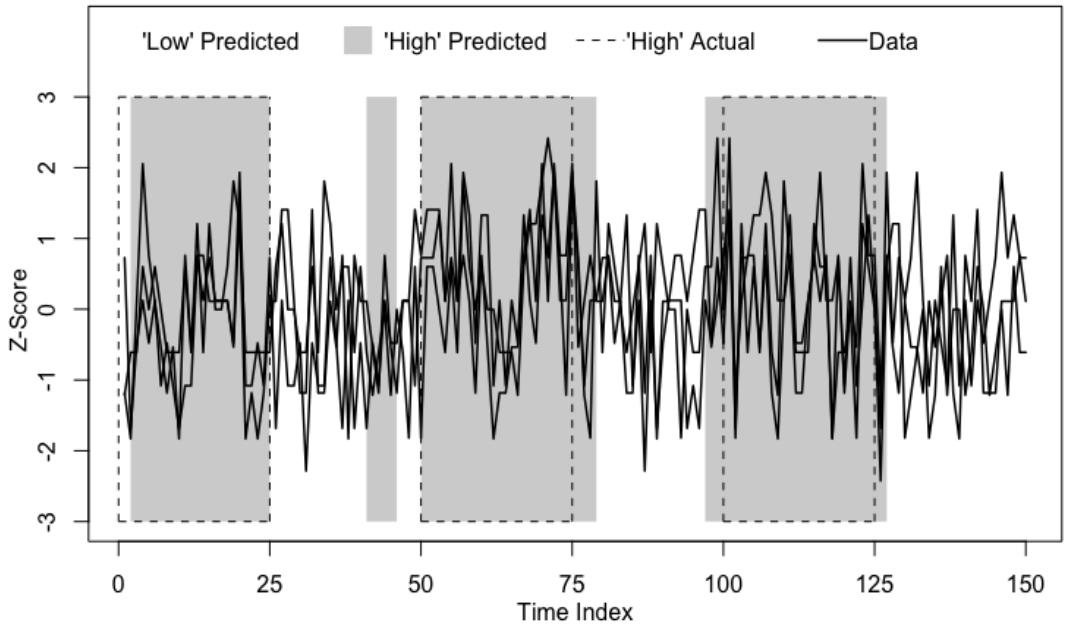

Figure A.3: Simulated test data superimposed on predicted and actual regimes (Study 2, $p = 3$).

Parameter	Symbol	Est.	SE	t	95% CI	p
L1 fixed (std.)	λ_1	1.00 (.75)	-	-	-	-
L2 unstd. (std.)	λ_2	1.11 (.77)	.22	5.1	(.68, 1.54)	<.001
L3 unstd. (std.)	λ_3	.99 (.65)	.20	5.0	(.60, 1.37)	<.001
MEV1 reg. 1	θ_{11}	1.02	.22	4.7	(.60, 1.45)	<.001
MEV2 reg. 1	θ_{21}	.89	.19	4.7	(.52, 1.26)	<.001
MEV3 reg. 1	θ_{31}	.82	.20	4.2	(.44, 1.20)	<.001
MEV1 reg. 2	θ_{12}	.43	.15	2.9	(.14, .73)	.002
MEV2 reg. 2	θ_{22}	.40	.13	3.1	(.15, .65)	.001
MEV3 reg. 2	θ_{32}	.58	.16	3.7	(.27, .90)	<.001
AR1 coefficient	ϕ_1	.06	.11	0.5	(-.16, .28)	.310
IE var.	ψ	.53	.17	3.1	(.20, .87)	.001
Log odds 1→1	$\ln(\frac{\pi_{11}}{1-\pi_{11}})$	2.31	.75	3.1	(.85, 3.77)	.001
Log odds 2→1	$\ln(\frac{\pi_{21}}{1-\pi_{21}})$	-2.79	.72	-3.9	(-4.20, -1.37)	<.001

Note: CI = confidence interval; Est. = estimate; IE = innovation error; L = loading; MEV = measurement error variance; p = p-value; reg. = regime; SE = standard error; std. = standardized; t = Student's t test statistic; unstd. = unstandardized; var. = variance

Table A.5: Parameter estimates from the AR(1) RSDFM fit to simulated test data (Study 2, $p = 3$).

The natural log odds of the regime transition probabilities (e.g., in Table A.4, $\ln(\frac{\pi_{11}}{1-\pi_{11}}) = 4.24$) can be converted to probability values. For example, $\frac{\exp(4.24)}{1+\exp(4.24)} = .986 = \pi_{11}$ is the estimated probability of staying in Regime 1 from one time point to the next. Knowing this, the probability of switching from Regime 1 to Regime 2 (π_{12}) can be computed by subtracting from 1 (i.e., $1 - .986 = .014$). Hence, the fact that the rows of the transition probability matrix must sum to 1 makes it possible to estimate only one log odds parameter per row of the transition probability matrix. The RSDFMs were also specified to estimate the log odds of switching from Regime 2 to Regime 1, or $\ln(\frac{\pi_{21}}{1-\pi_{21}})$, such as -4.24 in Table A.4. Converting this estimate to a probability as in the above example yields .014, the same as the probability of switching regimes in the reverse direction. Therefore, the probability of staying in Regime 2 is also .986. These probability estimates are consistent with the fact that the data were simulated to exhibit Regime 1 and Regime 2 for an equal number of time points, switching every 90 time points or approximately a .011 probability of switching in either direction (i.e., close to the estimated probability of .014).

A.3 Discussion

The analyses performed on the test data sets demonstrate the RSDFM as a highly worthwhile approach for analyzing collective synchrony. By deliberately introducing collective synchrony in the simulated time series within known intervals, it was possible to inspect the model's ability to correctly categorize low and high synchrony regimes and return parameter estimates consistent with expectations. Several findings are noteworthy. First, the RSDFM was able to identify the true regimes quite accurately overall. This was especially true with the Study 1 data, somewhat less so with the Study 2 data. Second, the Regime 2 parameter estimates quantifying the *magnitude* of collective synchrony, that

is, the explained variance in individual time series that can be attributed to the collective state variable, are consistent with the bivariate correlations among the simulated time series in Regime 2 intervals. Third, the Regime 1 parameter estimates quantifying the *unexplained* variance (i.e., measurement error variance) are consistent with the notion that in Regime 1, there is no latent collective process driving the individual time series. As such, the confidence intervals of those estimates should, and do, include 1 (i.e., 100%). Fourth, the parameter estimates of the natural log odds of the regime transition probabilities are consistent with the frequency of actual regime switches that were built into the simulated data. These findings are crucial in demonstrating that the RSDFM is a promising approach for categorizing time periods of high and low collective synchrony and quantifying features such as the strength (magnitude) of collective synchrony present in multivariate time series.

Two limitations should be noted. First, the RSDFM showed some inaccuracies at categorizing the regimes in the Study 2 data. This may be explained by the smaller number of time points, smaller number of time series (i.e., "persons"), smaller length of regime intervals, or some combination of these factors. Systematically testing the effects of these and possibly other factors using a Monte Carlo simulation study will be an important next step in establishing the RSDFM as a bona fide method for investigating collective synchrony. Second, in the simulated time series, regime intervals were uniform in length, and switches happened in a patterned way (i.e., after every 90 or every 25 time points), which would likely not be the case in actual performance settings. Nevertheless, the data sets were generated to mirror particular features of the empirical data including the number of persons, number of time points, and AR order/coefficients. Overall, this simulation demonstrated the promise of the RSDFM approach.

A.4 R Code for the Applied Simulation

```
##### Generate Study 1 Test Data #####
N <- 900
ny <- 6
test <- matrix(0, N, ny)
set.seed(02881)
for(i in 1:ny){
test[,i] <- arima.sim(list(order=c(2,0,0),
ar=c(runif(1, .5, .7), runif(1, -.20, 0))),
n=N, rand.gen=rnorm)
}
shocks <- runif(N/2,-2,2)
beg <- seq(181,N,180)
indices <- 1:90
for(i in beg){indices <- c(indices,i:(i+89))}
for(i in 1:ny){ # Introduce the "High synchrony" regime
test[indices,i] <- test[indices,i] + shocks
test[-indices,i] <- test[-indices,i] + runif(N/2,-2,2)
}
for(i in 1:ny){ # Convert to z-scores
test[,i] <- scale(test[,i])
}

##### Generate Study 2 Test Data #####
# N <- 150
# ny <- 3
# test <- matrix(0, N, ny)
# set.seed(02881)
# for(i in 1:ny){
# test[,i] <- arima.sim(list(order=c(2,0,0),
# ar=c(runif(1, 0, 0.4), runif(1, 0.2, 0.4))),
# n=N, rand.gen=rnorm)
# }
# shocks <- runif(N/2,-2,2)
# beg <- seq(51,N,50)
# indices <- 1:25
# for(i in beg){indices <- c(indices,i:(i+24))}
# for(i in 1:ny){ # Introduce the "High synchrony" regime
# test[indices,i] <- test[indices,i] + shocks
# test[-indices,i] <- test[-indices,i] + runif(N/2,-2,2)
# }
# for(i in 1:ny){ # Round to integers and convert to z-scores
# test[,i] <- round(test[,i])
```

```
# test[,i] <- scale(test[,i])
# }

test <- as.data.frame(test)
names(test) <- paste0("y",1:ncol(test))
ny <- ncol(test)
test$id <- rep(1,nrow(test))
test$time <- 1:nrow(test)

##### Two-Regime Model AR(2) #####
library(dynr)
ns <- 2
t_data <- dynr.data(test, id = "id", time = "time",
observed = names(test)[1:ny])

q1start <- .2
r1start <- runif(ny,1,2)
r2start <- runif(ny,0,.8)
recNoise <- prep.noise(values.latent =
list(diag(c(q1start,0), ns),
diag(c(q1start,0), ns)),
params.latent = list(diag(c(paste0("Q",1),0), ns),
diag(c(paste0("Q",1),0), ns)),
values.observed = list(diag(r1start, ny, ny),
diag(r2start, ny, ny)),
params.observed = list(diag(paste0("R",1:ny,1), ny, ny),
diag(paste0("R",1:ny,2), ny, ny)))

l2start <- runif(ny-1,.5,1.5)
recMeas <- prep.measurement(values.load = list(matrix(0, ny, ns),
matrix(c(1,l2start,rep(0,ny)), ny, ns)),
params.load = list(matrix(0, ny, ns),
matrix(c(0,paste0("L",2:ny),rep(0,ny)), ny, ns)),
obs.names = names(test)[1:ny],
state.names = c("C","Clag1"))

recReg <- prep.regimes(values = matrix(c(5, -4, 0, 0), 2, 2),
params = matrix(c("c11", "c21", "fixed", "fixed"), 2, 2))

recDyn <- prep.matrixDynamics(values.dyn =
list(matrix(c(.2,1,.1,0), ns, ns),
matrix(c(.2,1,.1,0), ns, ns)),
params.dyn = list(matrix(c("F1",0,"F2",0), ns, ns),
matrix(c("F1",0,"F2",0), ns, ns)),
```

```
isContinuousTime = FALSE)

recIni <- prep.initial(values.inistate=matrix(0, ns, 1),
params.inistate=matrix(0, ns, 1),
values.inicov=diag(1000, ns, ns),
params.inicov=diag(0, ns, ns),
values.regimep=c(5, -5),
params.regimep=c(0, 0))

rsmod <- dynr.model(dynamics = recDyn,
measurement = recMeas,
noise = recNoise,
initial = recIni,
regimes = recReg,
data = t_data,
outfile = "t_dynr.c")

t_dynr <- dynr.cook(rsmod, debug_flag=T)
summary(t_dynr)

##### Two-Regime Model AR(1) #####
library(dynr)
ns <- 1
t_data <- dynr.data(test, id = "id", time = "time",
observed = names(test)[1:ny])

q1start <- .2
r1start <- runif(ny,1,2)
r2start <- runif(ny,0,.8)
recNoise <- prep.noise(values.latent = list(diag(c(q1start), ns),
diag(c(q1start), ns)),
params.latent = list(diag(c(paste0("Q",1)), ns),
diag(c(paste0("Q",1)), ns)),
values.observed = list(diag(r1start, ny, ny),
diag(r2start, ny, ny)),
params.observed = list(diag(paste0("R",1:ny,1), ny, ny),
diag(paste0("R",1:ny,2), ny, ny)))

l2start <- runif(ny-1,.5,1.5)
recMeas <- prep.measurement(values.load = list(matrix(0, ny, ns),
matrix(c(1,l2start), ny, ns)),
params.load = list(matrix(0, ny, ns),
matrix(c(0,paste0("L",2:ny)), ny, ns)),
obs.names = names(test)[1:ny],
```

```
state.names = c("C"))

recReg <- prep.regimes(values = matrix(c(5, -4, 0, 0), 2, 2),
params = matrix(c("c11", "c21", "fixed", "fixed"), 2, 2))

recDyn <- prep.matrixDynamics(values.dyn =
list(matrix(c(.2), ns, ns),
matrix(c(.2), ns, ns)),
params.dyn = list(matrix(c("F1"), ns, ns),
matrix(c("F1"), ns, ns)),
isContinuousTime = FALSE)

recIni <- prep.initial(values.inistate=matrix(0, ns, 1),
params.inistate=matrix(0, ns, 1),
values.inicov=diag(1000, ns, ns),
params.inicov=diag(0, ns, ns),
values.regimep=c(5, -5),
params.regimep=c(0, 0))

rsmod <- dynr.model(dynamics = recDyn,
measurement = recMeas,
noise = recNoise,
initial = recIni,
regimes = recReg,
data = t_data,
outfile = "t_dynr.c")

t_dynr <- dynr.cook(rsmod, debug_flag=T)
summary(t_dynr)
```

List of References

[1] R Core Team, *R: A Language and Environment for Statistical Computing*, R Foundation for Statistical Computing, Vienna, Austria, 2017. [Online]. Available: http://www.R-project.org/

[2] L. Ou, M. D. Hunter, and S.-M. Chow, *dynr: Dynamic Modeling in R*, 2018, R package version 0.1.12-5. [Online]. Available: https://CRAN.R-project.org/package=dynr

[3] H. Akaike, "Information theory and an extension of the maximum likelihood principle," in *Selected Papers of Hirotugu Akaike*. Springer, 1998, pp. 199–213.

[4] G. Schwarz, "Estimating the dimension of a model," *The Annals of Statistics*, vol. 6, no. 2, pp. 461–464, 1978.

APPENDIX B

Supplementary Tables and Figures

Game	N	AR(1) DFM	AR(2) DFM	AR(1) RSDFM	AR(2) RSDFM	Selected Model
1	8	17105	16969	-	-	AR(2)DFM
2	6	12702	12586	12634	12530	AR(2)RSDFM
3	9	-	19116	19168	-	AR(2)DFM
4	5	10956	-	-	-	AR(1)DFM
5	5	10286	10204	10211	10125	AR(2)RSDFM
6	6	11808	11674	11761	-	AR(2)DFM
7	7	15258	15162	-	15098	AR(2)RSDFM
8	9	19396	19262	-	-	AR(2)DFM
9	7	-	15144	-	-	AR(2)DFM
10	6	12995	12872	12956	14580	AR(2)DFM
11	8	-	-	-	17591	AR(2)RSDFM
12	7	14240	14116	14104	13984	AR(2)RSDFM
13	4	7798	7727	7791	7667	AR(2)RSDFM
14	6	12934	12816	12891	-	AR(2)DFM
15	7	-	15179	-	-	AR(2)DFM
16	5	11400	11284	11342	11238	AR(2)RSDFM
17	4	8566	8483	8556	8468	AR(2)RSDFM
18	3	-	6666	6674	6596	AR(2)RSDFM

Note: The selected model for each data set (table row) is that with the smallest AIC value; missing AIC indicates that the model failed to converge during estimation or was discarded

Table B.1: Study 1 cadence models: sample sizes (N), AIC, selected model.

Game	N	AR(1) DFM	AR(2) DFM	AR(1) RSDFM	AR(2) RSDFM	Selected Model
1	8	17026	16934	16651	16565	AR(2)RSDFM
2	6	12656	12590	12517	12440	AR(2)RSDFM
3	9	18934	18837	18745	-	AR(1)RSDFM
4	5	-	10822	10753	-	AR(1)RSDFM
5	5	10115	10066	10004	9958	AR(2)RSDFM
6	6	11935	11874	11778	11687	AR(2)RSDFM
7	7	14935	14877	-	14755	AR(2)RSDFM
8	9	18809	18687	18699	-	AR(2)DFM
9	7	-	14918	14892	14804	AR(2)RSDFM
10	6	13159	13044	12948	12828	AR(2)RSDFM
11	8	17263	17141	17147	-	AR(2)DFM
12	7	14319	14193	14087	13965	AR(2)RSDFM
13	4	7742	7695	7621	7567	AR(2)RSDFM
14	6	-	13302	13228	-	AR(1)RSDFM
15	7	-	-	-	-	None
16	5	11399	11265	11307	-	AR(2)DFM
17	4	-	8634	8235	8200	AR(2)RSDFM
18	3	6703	6628	6598	6532	AR(2)RSDFM

Note: The selected model for each data set (table row) is that with the smallest AIC value; missing AIC indicates that the model failed to converge during estimation or was discarded

Table B.2: Study 1 distance models: sample sizes (N), AIC, selected model.

Game/Triad (Session)	AR(1) DFM	AR(2) DFM	VAR(1)	AR(1) RSDFM	AR(2) RSDFM	Selected Model
1. Av1 (1)	1209	1211	1276	-	-	AR(1)DFM
2. Av2 (1)	1268	1270	1289	-	-	AR(1)DFM
3. Av1 (3)	1283	1285	1323	-	-	AR(1)DFM
4. Bv1 (1)	1134	1136	1236	-	1128	AR(2)RSDFM
5. Bv1 (2)	1281	1283	1330	-	-	AR(1)DFM
6. Bv2 (2)	1277	1281	1291	-	-	AR(1)DFM
7. Bv2 (3)	1329	1333	1352	-	-	AR(1)DFM

Note: The selected model for each data set (table row) is that with the smallest AIC value; missing AIC indicates that the model failed to converge during estimation or was discarded

Table B.3: Study 2 models: AIC and selected model.

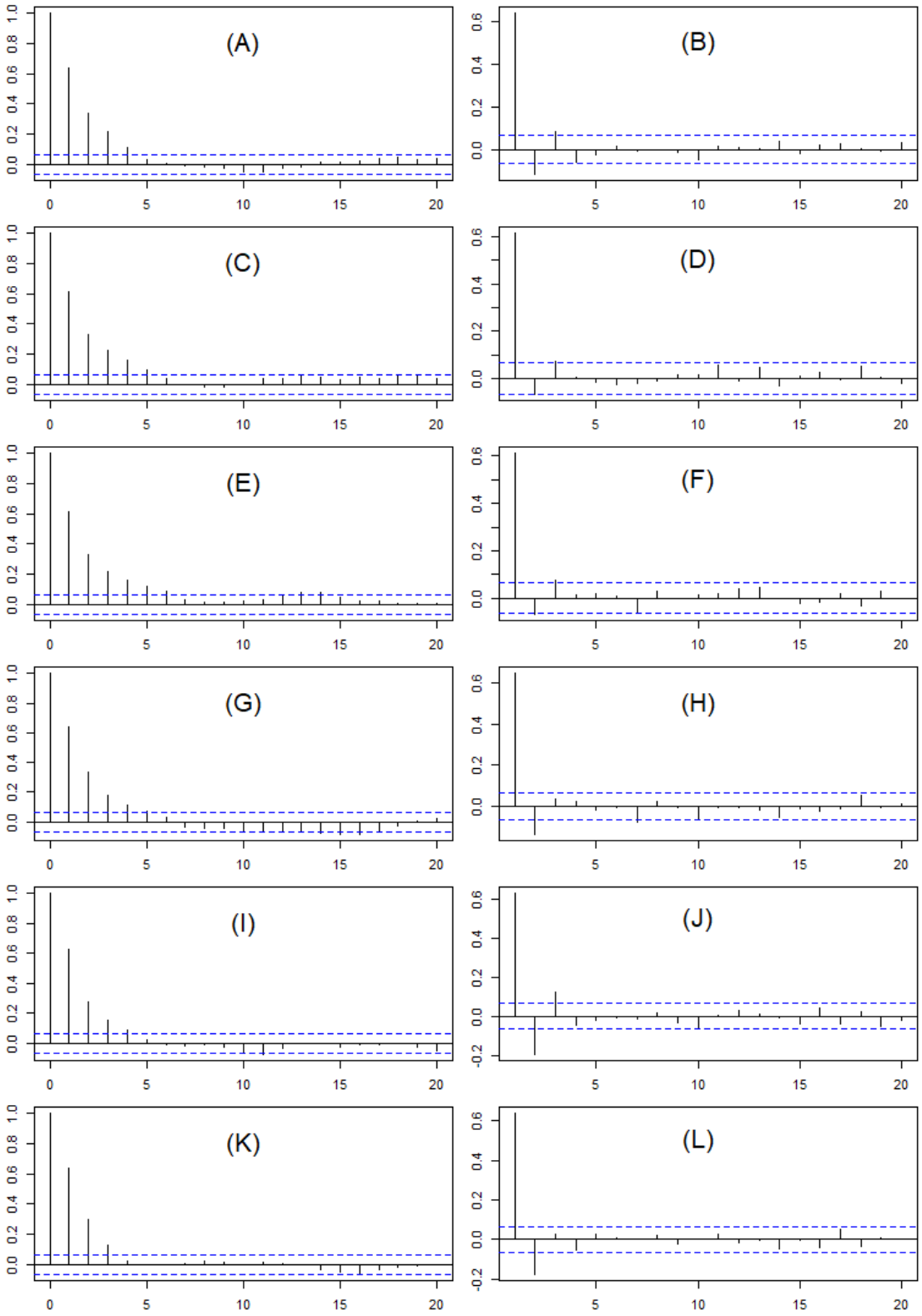

Figure B.1: Plots of ACF and PACF of cadence (upper 3 rows) and distance (lower 3 rows) time series data from Study 1; each row shows ACF (left) and PACF (right) side-by-side for a randomly selected participant; dashed lines indicate $p = .05$ significance limits.

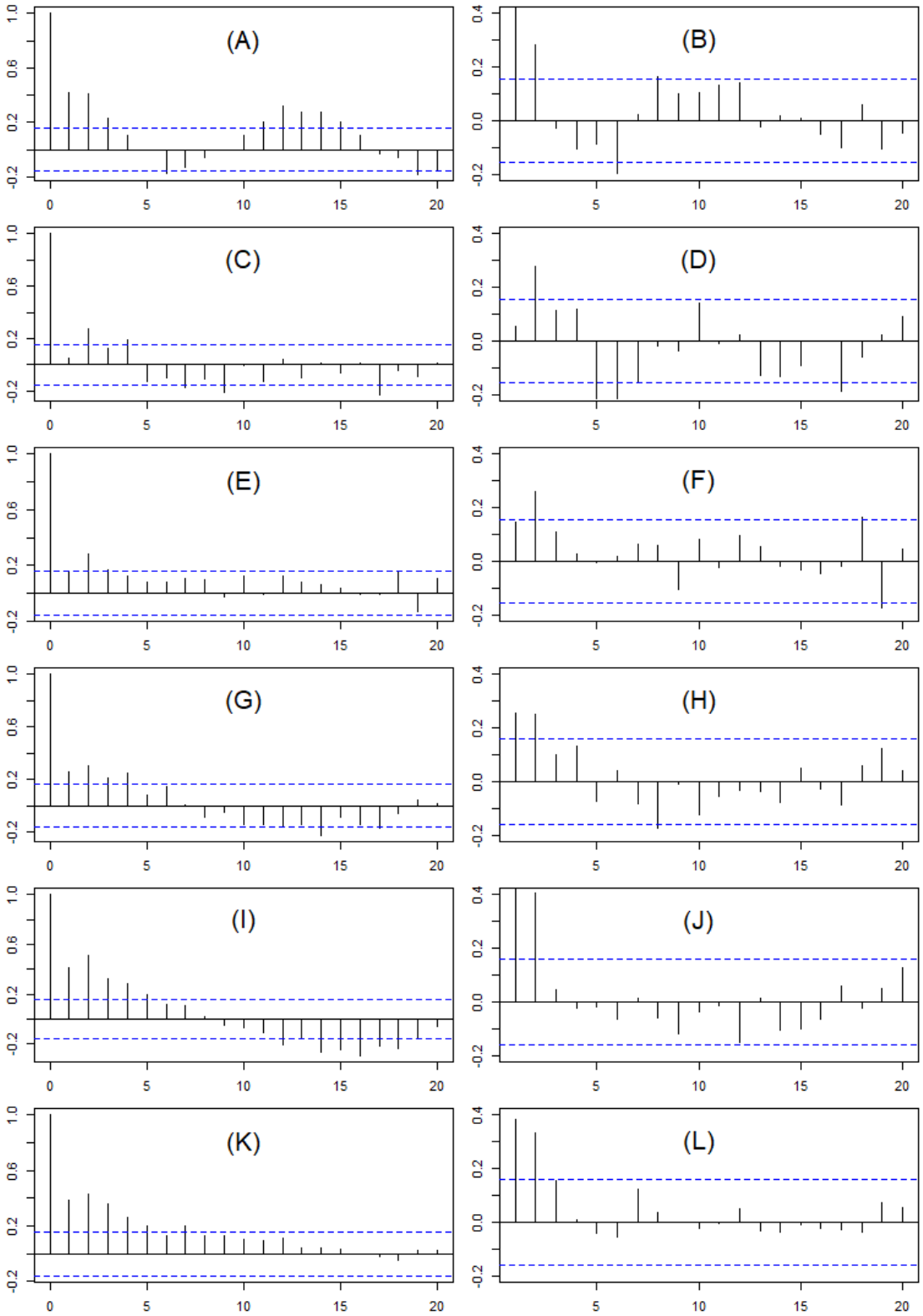

Figure B.2: Plots of ACF and PACF of change in heart rate from Triad A (upper 3 rows) and Triad B (lower 3 rows) time series data from Study 2; each row shows ACF (left) and PACF (right) side-by-side for a participant; dashed lines indicate $p = .05$ significance limits.

APPENDIX C

R Code for Study 1 and Study 2 Analyses

```
##### Study 1: cadence analysis #####
# note: code for distance analysis is comparable
library(dynr)
cadlist <- list(w1.cad,w2.cad,w3.cad,w4.cad,w5.cad,w6.cad,w7.cad,
w8.cad,w9.cad,w10.cad,w11.cad,w12.cad,w13.cad,w14.cad,w15.cad,
w16.cad,w17.cad,w18.cad)
for(i in 1:18){
rm(list=setdiff(ls(), c("i","cadlist","t1")))
# Extract data set and prep it for dynr routines
data <- cadlist[[i]]
data <- data[,-1]
p <- ncol(data)
T <- nrow(data)
names(data) <- paste0("y",1:p)
for(j in 1:p){
data[,j] <- scale(data[,j]) # turn observations to z-scores
}
data$id <- rep(1,T)
data$time <- 1:T
w_data <- dynr.data(data, id = "id", time = "time",
observed = names(data)[1:p])
tryCatch({
### AR1 RSDFM ###
k <- 1
qs <- runif(1)
r1s <- runif(p,.8,1.2)
r2s <- runif(p,0,.8)
recNoise <- prep.noise(values.latent = list(diag(c(qs), k),
diag(c(qs), k)),
params.latent = list(diag(c(paste0("psi")), k),
diag(c(paste0("psi")), k)),
values.observed = list(diag(r1s, p, p),
diag(r2s, p, p)),
params.observed = list(diag(paste0("theta",1:p,1), p, p),
diag(paste0("theta",1:p,2), p, p)))
ls <- runif(p-1,.5,1.5)
recMeas <- prep.measurement(values.load = list(matrix(0, p, k),
matrix(c(1,ls), p, k)),
```

```
params.load = list(matrix(0, p, k),
matrix(c(0,paste0("lambda",2:p)), p, k)),
obs.names = names(data)[1:p],
state.names = c("C"))
recReg <- prep.regimes(values = matrix(c(5, -4, 0, 0), 2, 2),
params = matrix(c("log11", "log21", "fixed", "fixed"), 2, 2))
recDyn <- prep.matrixDynamics(values.dyn =
list(matrix(c(.4), k, k),
matrix(c(.4), k, k)),
params.dyn = list(matrix(c("phi1"), k, k),
matrix(c("phi1"), k, k)),
isContinuousTime = FALSE)
recIni <- prep.initial(values.inistate=matrix(0, k, 1),
params.inistate=matrix(0, k, 1),
values.inicov=diag(1000, k, k),
params.inicov=diag(0, k, k),
values.regimep=c(5, -5),
params.regimep=c(0, 0))
ar1rsdfm <- dynr.model(dynamics = recDyn,
measurement = recMeas,
noise = recNoise,
initial = recIni,
regimes = recReg,
data = w_data,
outfile = "ar1rsdfm.c")
ar1rs <- dynr.cook(ar1rsdfm,verbose=F)
}, error=function(e){cat("ERROR :",conditionMessage(e), "\n")})
tryCatch({
### AR2 RSDFM ###
k <- 2
qs <- runif(1)
r1s <- runif(p,.8,1.2)
r2s <- runif(p,0,.8)
recNoise <- prep.noise(values.latent = list(diag(c(qs,0), k),
diag(c(qs,0), k)),
params.latent = list(diag(c(paste0("psi"),0), k),
diag(c(paste0("psi"),0), k)),
values.observed = list(diag(r1s, p, p),
diag(r2s, p, p)),
params.observed = list(diag(paste0("theta",1:p,1), p, p),
diag(paste0("theta",1:p,2), p, p)))
ls <- runif(p-1,.5,1.5)
recMeas <- prep.measurement(values.load = list(matrix(0, p, k),
matrix(c(1,ls,rep(0,p)), p, k)),
```

```
params.load = list(matrix(0, p, k),
matrix(c(0,paste0("lambda",2:p),rep(0,p)), p, k)),
obs.names = names(data)[1:p],
state.names = c("C","Cprev"))
recReg <- prep.regimes(values = matrix(c(5, -4, 0, 0), 2, 2),
params = matrix(c("log11", "log21", "fixed", "fixed"), 2, 2))
recDyn <- prep.matrixDynamics(values.dyn =
list(matrix(c(.6,1,-.2,0), k, k),
matrix(c(.6,1,-.2,0), k, k)),
params.dyn = list(matrix(c("phi1",0,"phi2",0), k, k),
matrix(c("phi1",0,"phi2",0), k, k)),
isContinuousTime = FALSE)
recIni <- prep.initial(values.inistate=matrix(0, k, 1),
params.inistate=matrix(0, k, 1),
values.inicov=diag(1000, k, k),
params.inicov=diag(0, k, k),
values.regimep=c(5, -5),
params.regimep=c(0, 0))
ar2rsdfm <- dynr.model(dynamics = recDyn,
measurement = recMeas,
noise = recNoise,
initial = recIni,
regimes = recReg,
data = w_data,
outfile = "ar2rsdfm.c")
ar2rs <- dynr.cook(ar2rsdfm,verbose=F)
}, error=function(e){cat("ERROR :",conditionMessage(e), "\n")})
tryCatch({
### AR1 DFM (Non-switching, i.e., one regime) ###
k <- 1
qs <- runif(1)
rs <- runif(p,0,.8)
recNoise <- prep.noise(values.latent = diag(c(qs), k),
params.latent = diag(c(paste0("psi")), k),
values.observed = diag(rs, p, p),
params.observed = diag(paste0("theta",1:p), p, p))
ls <- runif(p-1,.5,1.5)
recMeas <- prep.measurement(values.load = matrix(c(1,ls), p, k),
params.load = matrix(c(0,paste0("lambda",2:p)), p, k),
obs.names = names(data)[1:p],
state.names = c("C"))
recReg <- prep.regimes(values = matrix(c(0), 1, 1),
params = matrix(c(0), 1, 1))
recDyn <- prep.matrixDynamics(values.dyn = matrix(c(.4), k, k),
```

```
params.dyn = matrix(c("phi1"), k, k),
isContinuousTime = FALSE)
recIni <- prep.initial(values.inistate=matrix(0, k, 1),
params.inistate=matrix(0, k, 1),
values.inicov=diag(1000, k, k),
params.inicov=diag(0, k, k),
values.regimep=c(10),
params.regimep=c(0))
ar1_dfm <- dynr.model(dynamics = recDyn,
measurement = recMeas,
noise = recNoise,
initial = recIni,
regimes = recReg,
data = w_data,
outfile = "ar1_dfm.c")
ar1non <- dynr.cook(ar1_dfm,verbose=F)
}, error=function(e){cat("ERROR :",conditionMessage(e), "\n")})
tryCatch({
### AR2 DFM (Non-switching, i.e., one regime) ###
k <- 2
qs <- runif(1)
rs <- runif(p,0,.8)
recNoise <- prep.noise(values.latent = diag(c(qs,0), k),
params.latent = diag(c(paste0("psi"),0), k),
values.observed = diag(rs, p, p),
params.observed = diag(paste0("theta",1:p), p, p))
ls <- runif(p-1,.5,1.5)
recMeas <- prep.measurement(values.load =
matrix(c(1,ls,rep(0,p)), p, k),
params.load = matrix(c(0,paste0("lambda",2:p),rep(0,p)), p, k),
obs.names = names(data)[1:p],
state.names = c("C","Cprev"))
recReg <- prep.regimes(values = matrix(c(0), 1, 1),
params = matrix(c(0), 1, 1))
recDyn <- prep.matrixDynamics(values.dyn =
matrix(c(.6,1,-.2,0), k, k),
params.dyn = matrix(c("phi1",0,"phi2",0), k, k),
isContinuousTime = FALSE)
recIni <- prep.initial(values.inistate=matrix(0, k, 1),
params.inistate=matrix(0, k, 1),
values.inicov=diag(1000, k, k),
params.inicov=diag(0, k, k),
values.regimep=c(10),
params.regimep=c(0))
```

```
ar2_dfm <- dynr.model(dynamics = recDyn,
measurement = recMeas,
noise = recNoise,
initial = recIni,
regimes = recReg,
data = w_data,
outfile = "ar2_dfm.c")
ar2non <- dynr.cook(ar2_dfm,verbose=F)
}, error=function(e){cat("ERROR :",conditionMessage(e), "\n")})
### Save Environment ###
save.image(paste0("w",i,"c.RData"))
}

##### Study 2: change in heart rate analysis #####
library(dynr)
hrlist <- list(m1,m2,m3,m4,m5,m6,m7)
for(i in 1:length(hrlist)){
rm(list=setdiff(ls(), c("i","hrlist","t1")))
# Extract data set and prep it for dynr routines
data <- hrlist[[i]][,-1] # remove column 1 (timeofday)
data <- data[seq(1,nrow(data),10),] # remove repeated values
data <- data[seq(61,nrow(data),2),] # remove 1st min.; thin to .5 Hz
data <- data.frame(y1=scale(diff(data[,1])),
y2=scale(diff(data[,2])),
y3=scale(diff(data[,3])))
p <- ncol(data) # always 3 for Study 2 data
T <- nrow(data)
data$id <- rep(1,T)
data$time <- 1:T
m_data <- dynr.data(data, id = "id", time = "time",
observed = names(data)[1:p])
tryCatch({
### AR1 RSDFM ###
k <- 1
qs <- .1
r1s <- runif(p,.8,1.2)
r2s <- runif(p,.4,.8)
recNoise <- prep.noise(values.latent = list(diag(c(qs), k),
diag(c(qs), k)),
params.latent = list(diag(c(paste0("psi")), k),
diag(c(paste0("psi")), k)),
values.observed = list(diag(r1s, p, p),
diag(r2s, p, p)),
params.observed = list(diag(paste0("theta",1:p,1), p, p),
```

```
diag(paste0("theta",1:p,2), p, p)))
ls <- runif(p-1,.5,1.5)
recMeas <- prep.measurement(values.load = list(matrix(0, p, k),
matrix(c(1,ls), p, k)),
params.load = list(matrix(0, p, k),
matrix(c(0,paste0("lambda",2:p)), p, k)),
obs.names = names(data)[1:p],
state.names = c("C"))
recReg <- prep.regimes(values = matrix(c(2, -4, 0, 0), 2, 2),
params = matrix(c("log11", "log21", "fixed", "fixed"), 2, 2))
recDyn <- prep.matrixDynamics(values.dyn = list(matrix(c(.7), k, k),
matrix(c(.7), k, k)),
params.dyn = list(matrix(c("phi1"), k, k),
matrix(c("phi1"), k, k)),
isContinuousTime = FALSE)
recIni <- prep.initial(values.inistate=matrix(0, k, 1),
params.inistate=matrix(0, k, 1),
values.inicov=diag(1000, k, k),
params.inicov=diag(0, k, k),
values.regimep=c(-5, 5),
params.regimep=c(0, 0))
ar1rsdfm <- dynr.model(dynamics = recDyn,
measurement = recMeas,
noise = recNoise,
initial = recIni,
regimes = recReg,
data = m_data,
outfile = "ar1rsdfm.c")
ar1rs <- dynr.cook(ar1rsdfm,verbose=FALSE,debug_flag=TRUE)
}, error=function(e){cat("ERROR :",conditionMessage(e), "\n")})
tryCatch({
### AR2 RSDFM ###
k <- 2
qs <- .1
r1s <- runif(p,.8,1.2)
r2s <- runif(p,.4,.8)
recNoise <- prep.noise(values.latent = list(diag(c(qs,0), k),
diag(c(qs,0), k)),
params.latent = list(diag(c(paste0("psi"),0), k),
diag(c(paste0("psi"),0), k)),
values.observed = list(diag(r1s, p, p),
diag(r2s, p, p)),
params.observed = list(diag(paste0("theta",1:p,1), p, p),
diag(paste0("theta",1:p,2), p, p)))
```

```
ls <- runif(p-1,.5,1.5)
recMeas <- prep.measurement(values.load = list(matrix(0, p, k),
matrix(c(1,ls,rep(0,p)), p, k)),
params.load = list(matrix(0, p, k),
matrix(c(0,paste0("lambda",2:p),rep(0,p)), p, k)),
obs.names = names(data)[1:p],
state.names = c("C","Cprev"))
recReg <- prep.regimes(values = matrix(c(2, -4, 0, 0), 2, 2),
params = matrix(c("log11", "log21", "fixed", "fixed"), 2, 2))
recDyn <- prep.matrixDynamics(values.dyn =
list(matrix(c(.3,1,.4,0), k, k),
matrix(c(.3,1,.4,0), k, k)),
params.dyn = list(matrix(c("phi1",0,"phi2",0), k, k),
matrix(c("phi1",0,"phi2",0), k, k)),
isContinuousTime = FALSE)
recIni <- prep.initial(values.inistate=matrix(0, k, 1),
params.inistate=matrix(0, k, 1),
values.inicov=diag(1000, k, k),
params.inicov=diag(0, k, k),
values.regimep=c(-5, 5),
params.regimep=c(0, 0))
ar2rsdfm <- dynr.model(dynamics = recDyn,
measurement = recMeas,
noise = recNoise,
initial = recIni,
regimes = recReg,
data = m_data,
outfile = "ar2rsdfm.c")
ar2rs <- dynr.cook(ar2rsdfm,verbose=FALSE,debug_flag=TRUE)
}, error=function(e){cat("ERROR :",conditionMessage(e), "\n")})
tryCatch({
### AR1 DFM (Non-switching, i.e., one regime) ###
k <- 1
qs <- .1
rs <- runif(p,.4,.8)
recNoise <- prep.noise(values.latent = diag(c(qs), k),
params.latent = diag(c(paste0("psi")), k),
values.observed = diag(rs, p, p),
params.observed = diag(paste0("theta",1:p), p, p))
ls <- runif(p-1,.5,1.5)
recMeas <- prep.measurement(values.load = matrix(c(1,ls), p, k),
params.load = matrix(c(0,paste0("lambda",2:p)), p, k),
obs.names = names(data)[1:p],
state.names = c("C"))
```

```
recReg <- prep.regimes(values = matrix(c(0), 1, 1),
params = matrix(c(0), 1, 1))
recDyn <- prep.matrixDynamics(values.dyn = matrix(c(.7), k, k),
params.dyn = matrix(c("phi1"), k, k),
isContinuousTime = FALSE)
recIni <- prep.initial(values.inistate=matrix(0, k, 1),
params.inistate=matrix(0, k, 1),
values.inicov=diag(1000, k, k),
params.inicov=diag(0, k, k),
values.regimep=c(10),
params.regimep=c(0))
ar1_dfm <- dynr.model(dynamics = recDyn,
measurement = recMeas,
noise = recNoise,
initial = recIni,
regimes = recReg,
data = m_data,
outfile = "ar1_dfm.c")
ar1non <- dynr.cook(ar1_dfm,verbose=FALSE,debug_flag=TRUE)
}, error=function(e){cat("ERROR :",conditionMessage(e), "\n")})
tryCatch({
### One-regime VAR model ###
k <- 3
qs <- runif(k)
recNoise <- prep.noise(values.latent = diag(c(qs), k),
params.latent = diag(c(paste0("psi",1:k)), k),
values.observed = diag(0, p, p),
params.observed = diag(0, p, p))
recMeas <- prep.measurement(values.load = diag(1, p, k),
params.load = matrix(0, p, k),
obs.names = names(data)[1:p],
state.names = c("e1","e2","e3"))
recReg <- prep.regimes(values = matrix(c(0), 1, 1),
params = matrix(c(0), 1, 1))
recDyn <- prep.matrixDynamics(values.dyn = diag(c(.7,.6,.8), k, k),
params.dyn = diag(c("phi1","phi2","phi3"), k, k),
isContinuousTime = FALSE)
recIni <- prep.initial(values.inistate=matrix(0, k, 1),
params.inistate=matrix(0, k, 1),
values.inicov=diag(1000, k, k),
params.inicov=diag(0, k, k),
values.regimep=c(10),
params.regimep=c(0))
wndfm <- dynr.model(dynamics = recDyn,
```

```
measurement = recMeas,
noise = recNoise,
initial = recIni,
regimes = recReg,
data = m_data,
outfile = "wndfm.c")
wnnon <- dynr.cook(wndfm)
}, error=function(e){cat("ERROR :",conditionMessage(e), "\n")})
tryCatch({
### AR2 DFM (Non-switching, i.e., one regime) ###
k <- 2
qs <- .1
rs <- runif(p,.4,.8)
recNoise <- prep.noise(values.latent = diag(c(qs,0), k),
params.latent = diag(c(paste0("psi"),0), k),
values.observed = diag(rs, p, p),
params.observed = diag(paste0("theta",1:p), p, p))
ls <- runif(p-1,.5,1.5)
recMeas <- prep.measurement(values.load =
matrix(c(1,ls,rep(0,p)), p, k),
params.load = matrix(c(0,paste0("lambda",2:p),rep(0,p)), p, k),
obs.names = names(data)[1:p],
state.names = c("C","Cprev"))
recReg <- prep.regimes(values = matrix(c(0), 1, 1),
params = matrix(c(0), 1, 1))
recDyn <- prep.matrixDynamics(values.dyn =
matrix(c(.3,1,.4,0), k, k),
params.dyn = matrix(c("phi1",0,"phi2",0), k, k),
isContinuousTime = FALSE)
recIni <- prep.initial(values.inistate=matrix(0, k, 1),
params.inistate=matrix(0, k, 1),
values.inicov=diag(1000, k, k),
params.inicov=diag(0, k, k),
values.regimep=c(10),
params.regimep=c(0))
ar2_dfm <- dynr.model(dynamics = recDyn,
measurement = recMeas,
noise = recNoise,
initial = recIni,
regimes = recReg,
data = m_data,
outfile = "ar2_dfm.c")
ar2non <- dynr.cook(ar2_dfm,verbose=FALSE,debug_flag=TRUE)
}, error=function(e){cat("ERROR :",conditionMessage(e), "\n")})
```

```
# Save Environment
save.image(paste0("m",i,"h.RData"))
}
```