UNDERSTANDING THE SUCCESSFUL COORDINATION OF TEAM BEHAVIOR

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UNDERSTANDING THE SUCCESSFUL COORDINATION OF TEAM BEHAVIOR

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Collaborative art: freshly painted acrylic photographed against the sunlight.

In many areas of human life, people perform in teams. These teams' performances depend, at least partly, on team members' abilities to coordinate their contributions effectively. This includes the making of decisions and the regulation of behavior in reference to the framework provided by the social group- and task-context. Given the high relevance of a deepened and integrated understanding about the mechanisms underlying coordinated team behavior, the aim of this research topic is to provide a platform for different theoretical and methodological approaches to researching and understanding coordinated team behavior in different task contexts. The articles published in this edition offer a multifaceted insight into current work on the topic.

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EDITORIAL
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Check for updates

Editorial: Understanding the Successful Coordination of Team Behavior

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Keywords: team work, team sports, group, decision making, performance

Editorial on the Research Topic

Understanding the Successful Coordination of Team Behavior

In many areas of human life, people perform in teams. These teams' performances depend, at least partly, on team members' abilities to coordinate their contributions effectively (e.g., Steiner, 1972; Kravitz and Martin, 1986). This includes the making of decisions and the regulation of behavior in reference to the framework provided by the social group- and task-context (Wieber et al., 2012). Given the high relevance of a deepened and integrated understanding about the mechanisms underlying coordinated team behavior, the aim of this research topic is to provide a platform for different theoretical and methodological approaches to researching, describing, and understanding coordinated team behavior in different task contexts.

The 11 contributions accepted for publication in this Research Topic demonstrate that the understanding of coordinated team behavior defines a broad area of research: The researched teams are manifold and include rowing teams, soccer teams, rope skipping teams, baseball teams, scientific research teams, teams operating unmanned aerial vehicles, dyads that visually track multiple objects, and more. The diversity of the paradigms and approaches employed in the contributing articles does not fall short of that of the researched teams. This diversity illustrates the many considerable aspects of team coordination and signifies that various approaches are necessary to enable insights into the mechanisms potentially underlying team coordination in different situations. Although the employed approaches do differ from each other, they unite in their goal of overcoming the challenges that are associated with research on team coordination. Among others, these challenges include the actual measurement of coordination and the often limited accessibility of the underlying processes. In the following, examples of how these challenges are tackled shall be given to provide a short introduction into this Research Topic.

To assess the coordination of baseball infielders, Gray et al. use a novel joint decision paradigm involving a dedicated scoring system based on expert ratings of team coordination. By experimentally manipulating the composition of teams, the effects of previous common experiences on joint decisions are tested. In another experimental approach, Wahn et al. operationalize team coordination by the object-tracking performance of dyads. In the employed task, performance scores increase the more efficiently the partners divide task demands. Wahn et al. test how sharing (receiving) information about co-actors' actions and the team score affects team performance. Additionally, they test for differences in the effectiveness of specific coordination strategies over time.

Three contributions engage in network analysis. Pina et al. measure team performance by discriminating between successful and unsuccessful offensive plays in association football. They use social network analyses to calculate variables describing a team's passing network and test the predictive value of these network variables for the successfulness of team performance.

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Li et al. consider co-authorships of published articles as an indicator of team knowledge creation. Social network analysis is used to calculate variables describing the co-author networks and to test relations between network variables and team knowledge creation. Ramos et al. assent to the contributions of social networks analysis to understanding team behavior. With the goal of further expanding the capabilities of this methodological approach, the authors evaluate the use of hypernetworks that simultaneously access cooperative and competitive interactions between teammates and adversaries across space and time and on various levels of analysis.

In a case study involving a newly assembled rowing crew, Feigean et al. use boat velocity as a performance measure. They describe changes of the crew performance after a 6-week training interval and explore to which extent practice induced team benefits are obtained through distinct individual adaptions of the rowing patterns.

Stevens and Galloway use EEG data of the members of performing teams to quantitating the teams' neurodynamic organizations. Individual EEG data linked to measures of social coordination during the evolution of performed tasks are transformed into symbolic information units about the team's neural organization and synchronization. The authors discuss the potential the results raise for developing quantitative models of team dynamics that enable comparisons across teams and tasks.

Gesbert et al. adopt a phenomenological approach to explore how soccer players' lived experiences are linked to the active regulation of team coordination during offensive transition situations. They present different collective regulation modes that result from the qualitative analyses of the athletes' phenomenological reports.

Reviewing empirical findings, Gorman et al. illustrate the use of viewing teams as dynamical systems for understanding the coordination principles underlying teamwork. They advocate a systems perspective on teamwork that is based on general coordination principles lying within the individuals and present a framework for understanding and modeling teams as dynamical systems.

Steiner et al. provide an integrative perspective on coordination in interactive sport teams and define a framework that considers the coexisting contributions of shared mental models, situation-specific (ecological) information and individuals' constructionist perspectives on current game situations to enabling team coordination.

Bowers et al.'s contribution is dedicated to team resilience. The concept is used to explain why and how teams are able to maintain performance levels when facing adversity in the form of specific stressors. The authors provide a theoretical model of team resilience as an emergent state at the group level.

The contributions to this Research Topic offer a multifaceted insight into current research on team coordination and team functioning. We hope that they inspire further research on the topic as much remains to be learned about the successful coordination of team behavior. The many areas of human life in which performance is delivered by teams adumbrates the large field of application that could benefit from a deepened understanding.

AUTHOR CONTRIBUTIONS

SS, RS, and NC contributed to the ms and gave final approval of the version to be submitted.

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ORIGINAL RESEARCH
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Investigating Team Coordination in Baseball Using a Novel Joint Decision Making Paradigm

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A novel joint decision making paradigm for assessing team coordination was developed and tested using baseball infielders. Balls launched onto an infield at different trajectories were filmed using four video cameras that were each placed at one of the typical positions of the four infielders. Each participant viewed temporally occluded videos for one of the four positions and were asked to say either "ball" if they would attempt to field it or the name of the bag that they would cover. The evaluation of two experienced coaches was used to assign a group coordination score for each trajectory and group decision times were calculated. Thirty groups of 4 current college baseball players were: (i) teammates (players from same team/view from own position), (ii) non-teammates (players from different teams/view from own position), or (iii) scrambled teammates (players from same team/view not from own position). Teammates performed significantly better (i.e., faster and more coordinated decisions) than the other two groups, whereas scrambled teammates performed significantly better than non-teammates. These findings suggest that team coordination is achieved through both experience with one's teammates' responses to particular events (e.g., a ball hit up the middle) and one's own general action capabilities (e.g., running speed). The sensitivity of our joint decision making paradigm to group makeup provides support for its use as a method for studying team coordination.

Keywords: teamwork, coordination, cognition, sports, decision making

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INTRODUCTION

Whether executing a "set piece" in soccer, playing a zone defense in football, or turning a double play in baseball, effective performance in team sports hinges on the development of team cognition. Team cognition is the cognitive activity at the team level and is shared amongst team members through interactions in the form of direct or indirect communication and coordination (Cooke et al., 2013). To date, our understanding of team cognition has been limited by the methodologies used to study it which tend to fall into one of two categories (reviewed in McNeese et al., 2016, 2017): (i) knowledge elicitation methods which pool and aggregate the passive responses of individual teammates taken out of context to assess shared mental models (Cannon-Bowers et al., 1993), or (ii) techniques which analyze the macro level behavior of teammates during actual gameplay (e.g., the movements of players from GPS data), but do little to elucidate the underlying perceptual-cognitive processes. The goal of the present study was to develop and test a new paradigm for studying team coordination that represents a middle ground between these two extremes.

A key element of team cognition is coordinated decision making, or as players often refer to: "being on the same page." An example of the importance of coordinated decision making can be seen on the baseball field. As illustrated in **Figure 1**, when a ball is hit on the ground and there are runners on base, each of the four infielders must rapidly decide between two options: (i) attempting to move to intercept ("field") the ball, or (ii) moving toward ("covering") one of bases in preparation to receive a throw. For the two middle infielders (i.e., the shortstop and second baseman) there is further complexity in that they must also decide which base to cover (e.g., a shortstop needs to cover second base if the second baseman fields the ball and third base if the third baseman fields it). In this situation, it is possible to assess the "correctness" of an individual player's decision — if a player is closest to the ball and decides to field it we could consider it to be a correct decision. However, successfully making an out on the play hinges more on the overall coordination of the teammates' decisions as opposed to their individual correctness (e.g., if a different player is going to field the ball the overall outcome would be better if the closest player decides to cover a bag). Team decision making in a baseball infield is a prime example of Interactive Team Cognition (ITC) which proposes that team cognition is a dynamic team level activity that is inseparable from the context in which it occurs (Cooke et al., 2013).

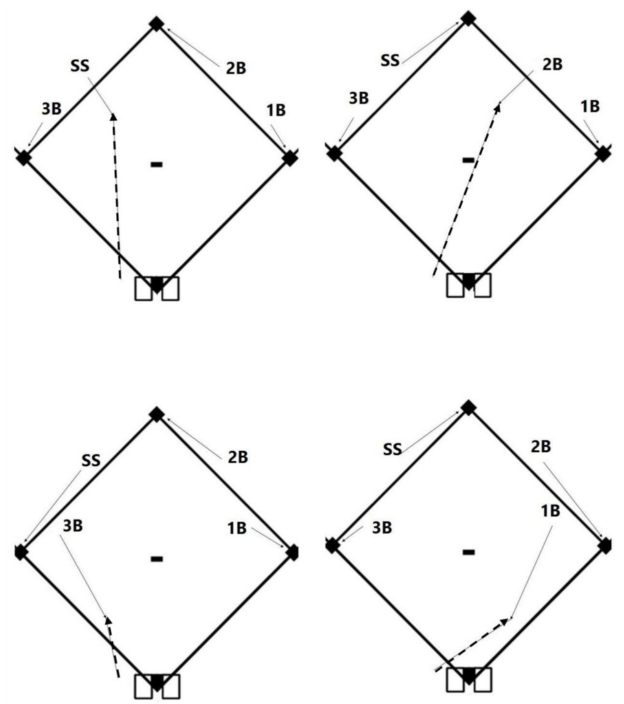

FIGURE 1 | Illustration of coordination in a baseball infield. Depending on the trajectory of the batted ball (dashed lines), each player must decide whether to attempt to move to intercept the ball (i.e., "field it") or to move so that they can receive a ball thrown to one of the bases (black diamonds). Each of the four panels illustrates how players are typically taught to move (dotted lines) depending on which player fields the ball. 1B = first baseman, 2B = second baseman, SS = shortstop, 3B = third baseman.

As we have proposed previously (McNeese et al., 2016), a fruitful approach for studying team coordination in this context may be to "scale up to a team level" methods that have proven to be effective for assessing perceptual-cognitive processes in individual athletes. For example, the occlusion paradigm has been used to study anticipation and decision making in sports (Abernethy and Russell, 1984). This paradigm involves having an individual view an unfolding event (e.g., an opponent serving a tennis ball) either on video or live, and spatially (e.g., blocking the view of the server's legs for the entire serve) or temporally (e.g., completely blocking view of the server after 500 ms) occluding the event. Then, asking the viewer to make a decision using either a passive (e.g., saying "down the line or cross court") or active (e.g., stepping in the anticipated direction of ball travel) response. As reviewed in Farrow and Abernethy (2015), this methodology has been used to understand expertise differences in decision making, anticipation and gaze behavior (at the individual athlete level) for both one-on-one (e.g., tennis or squash serves, soccer penalty kicks) and sporting actions involving multiple players (e.g., deciding whom to pass the ball to in basketball).

In the present study, we extended this occlusion paradigm to create and test a novel method for assessing coordinated decision making in sports. Specifically, a video of an unfolding event (a ball hit onto a baseball infield) was simultaneously filmed from multiple locations, each corresponding to the position of one of the four infielders. Experienced baseball players (in groups of four) were then asked to make coincident decisions (either play the ball or cover a bag) while watching temporally occluded videos of balls hit at different trajectories. The evaluation of two experienced coaches were used to assign a coordination score for each trajectory for each group. In addition, mean decision times were also calculated. Coordination scores ranged from 3-indicating effective coordination (i.e., all bases covered and player identified by the coaches goes for ball) to 0-indicating poor coordination (i.e., no player goes for ball). There were 3 types of groups: (i) *teammates* (players from same team who each viewed videos from the camera location corresponding to their own playing position), (ii) *non-teammates* (players from different teams who viewed videos corresponding to their own position), and (iii) *scrambled teammates* (players from the same team that viewed videos from a camera position that did not correspond to their own playing position). The main goal of the study was validate this new joint decision making paradigm by determining whether or not it is sensitive to group makeup (e.g., teammates vs. non-teammates). Based on the assumption that it would be sensitive, we made the following specific predictions:

(i) The teammate group would have significantly higher coordination scores and significantly faster decision times as compared to the other two groups due to their knowledge of how their teammates act in different game situations and their action capabilities.
(ii) The non-teammates group would have significantly higher coordination scores and significantly faster decision times than the scrambled teammates group because they had more experience playing the viewed position.

MATERIALS AND METHODS

Participants

The participants in the study were 120 male baseball players who played for Division 1 college baseball teams affiliated with the National Junior College Athletic Association (NJCAA, United States) at the time of participation. The mean age of these participants was 20.7 ($SD = 2.1$), the mean number of years of competitive playing experience was 12.2 ($SD = 1.8$), and the mean fielding percentage was 0.92. This study was carried out in accordance with the recommendations of the Arizona State University Institutional Review Board with written informed consent from all subjects. All subjects gave written informed consent in accordance with the Declaration of Helsinki. The protocol was approved by the Arizona State University Institutional Review Board.

The 120 participants were divided into 30 groups of four players, with each group having one first baseman, one second baseman, one shortstop, and one third baseman. There were three group types:

Teammates – four players who currently played on the same team together and were asked to make judgments from the viewing perspective of their own position. The 10 groups of this type had a mean age of 21.9 ($SD = 2.3$), a mean number of years of playing experience of 12.8 ($SD = 1.7$) and a mean fielding percentage of 0.91. On average, each group has been playing together as teammates for 1.1 ($SD = 0.5$) years at the time of the study.

Non-teammates – four players who currently did not play on the same team together and were asked to make judgments from the viewing perspective of their own position. The 10 groups of this type had a mean age of 20.9 ($SD = 2.0$), a mean number of years of playing experience of 11.6 ($SD = 2.0$) and a mean fielding percentage of 0.93. These groups were formed randomly with the only requirements being that all members currently played for a Division 1 NJCAA team and that all four infield position were represented in each group.

Scrambled Teammates – four players who currently played on the same team together and were asked to make judgments from the viewing perspective different from their own position. The 10 groups of this type had a mean age of 22.0 ($SD = 1.9$), a mean number of years of playing experience of 12.9 ($SD = 2.1$) and a mean fielding percentage of 0.92. On average, each group has been playing together as teammates for 1.2 ($SD = 0.5$) years at the time of the study.

One-way ANOVAs revealed that there were no significant differences in age, years of playing experience, or fielding percentage for the three groups, p's all >0.5, all η_p^2 's all <0.1.

Apparatus

Each participant viewed HD videos presented on a 61 cm (24″) Dell Ultra monitor (resolution 1024 × 768) of standard baseballs being projected from a ball launching machine (Sports Tutor ProLite™). Participants watched the videos while seated from a viewing distance of 57 cm. No chin rest was used. Balls were projected at a speed of 11 m/s (25 mph) onto the ground of 15 m (50 ft) side-length, practice baseball diamond. As illustrated in **Figure 2**, there were 7 different lateral launch angles (−36, −24, −12, 0, 12, 24, and 36°), where −45° was the left field line, 0° was over second base and 45° was the right field line. Balls were filmed simultaneously using four Go Pro Hero 4 cameras with 1080p resolution and 60 frames per second. Only the ball and the field were shown in the videos (i.e., the other cameras and players were not visible). The cameras were mounted on tripods and placed in the standard positions of the four infielders. Specifically, each camera was placed 3 m (10 ft) behind and 3 m to the side of the base. The camera height was 1 m, a value chosen to represent the eye height of an average infielder when they are in the "ready position" (i.e., knees and back bent, glove at knee level). **Table 1** shows the approximate launch angles from each of the four infielder/camera locations. Videos were edited so that the view of the ball was occluded and replaced with a mask (a pattern of random black and white dots) after 250 ms. The mask remained on the screen until the player made a response after which the screen was blanked. The inter-trial interval was 500 ms. The viewing duration was chosen based on previous research using temporal occlusion to investigate the return of a tennis serve (e.g., Farrow et al., 2005) which has employed

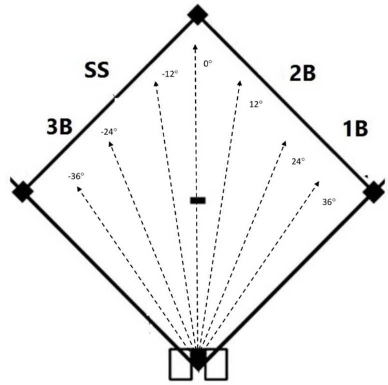

FIGURE 2 | Illustration of the hit trajectories used in the videos. On each trial, a ball was launched onto the ground from home plate (black diamond at bottom of figure) at one of 7 possible angles (dashed lines) with an angle of 0° being a ball hit directly straight ahead over second base (black diamond at top of figure). The 1B (first baseman), 2B (second baseman), SS (shortstop), and 3B (third baseman) show the approximate positions of the four cameras.

TABLE 1 | Approximate ball trajectory angles (in degrees) from each viewing position.

Home	1B	2B	SS	3B
−36	−66	−54	−18	−6
−24	−54	−42	−6	6
−12	−42	−30	6	18
0	−30	−18	18	30
12	−18	−6	30	42
24	−6	6	42	54
36	6	18	54	66

viewing windows of 200–300 ms. To our knowledge, there is no previous research which has used temporal occlusion to study baseball fielding. In the arrangement used in the present study, a ball launched directly at the camera would reach the camera location in roughly 1.6 s for the first and third base locations and 1.9 s for the shortstop and second base locations. Therefore, the 250 ms viewing duration represented approximately 15% of the total flight time for the first and third base positions and 13% of the flight time for the shortstop and second base positions.

Procedure

Participants were instructed that their task was to verbally indicate as quickly and accurately as possible what they would do for each ground ball. Participants were given two response choices: say "ball" if they would attempt to field the ball, or say the name of the base they would cover if they decided they would let another player on the infield field it. They were further instructed to assume that the other infielders were in their "standard positions in a situation in which the bases were loaded and there were 0 outs." Responses were recorded using an Audio-Technica PRO 8HEcW headset microphone and audio files were analyzed using a PsychoPy to determine reaction time and ensure synchronization between the videos and audio recordings. After completing 5 practice trials, all participants completed 70 experimental trials representing 10 presentations of the 7 different trajectories presented in random order. Participants were told that they would be performing the experiment simultaneously (in different rooms) with the other three players in their group who would be viewing the videos from different angles. The four participants viewed the videos on separate monitors and could not hear the responses made by the other participants. At no time did participants receive feedback about their responses. For the teammates and non-teammates groups, each player viewed the video from the camera corresponding to their own position. With reference to **Figure 2**, for the scrambled teammates group, the first baseman (1B) viewed the video shot from the shortstop's (SS) perspective (and vice versa) and the second baseman (2B) viewed the video shot from the third baseman's (3B) perspective (and vice versa). Each group of four participants waited together (and were free to converse with each other) for 15 min before the study began. They were not told about the specifics of the experiment until they were in separate rooms and were not given a chance to talk to each other again until the experiment was completed.

Data Analysis

Two different dependent measures were used: coordination score and decision time. Coordination score was a measure of the combined effectiveness of the responses made by the group of four players. To calculate this, we first had two experienced NJCAA baseball coaches watch the videos of the 7 ball trajectories (with no occlusion) and indicate which infielder they felt should attempt to field the ball assuming equal skills among all teammates. These assessments were highly consistent with the coaches producing the same response for all 7 trajectories[1]. The coaches' choices were then used to assess the group response on each trial using the following scoring system:

3 points: Coaches' choice player goes for the ball, all bags covered by other players in the group.
2 points: Player other than coaches' choice goes for the ball, all bags covered by other players in group.
1 point: Two or more players in group indicate they would get the ball (therefore, not all bags covered).
0 point: No players in the group indicate they would get the ball.

Mean coordination scores were then calculated for each trajectory by averaging the score for the 10 repeats. Mean decision times were calculated for each trajectory by averaging the times for the four participants then averaging across the 10 repeats. These variables were then analyzed using separate 3 × 7 mixed ANOVAs with group (teammates, non-teammates and scrambled teammates) as a between subjects factors and launch angle as the within subjects factor.

RESULTS

Figure 3 shows the mean coordination score for the three groups plotted as a function of launch angle. The ANOVA performed on these data revealed a significant main effect of group, $F(2,27) = 23.8$, $p < 0.001$, $\eta_p^2 = 0.64$. Independent samples t-tests (with Bonferroni correction, $p = 0.017$) revealed that the coordination score was significantly higher for the teammates group as compared to both the non-teammates, $t(18) = 7.4$, $p < 0.001$, $d = 3.3$, and scrambled teammates, $t(18) = 3.9$, $p = 0.001$, $d = 1.8$, groups. Furthermore, the coordination score for the scrambled teammates group was significantly higher than for the non-teammates, $t(18) = 2.9$, $p = 0.009$, $d = 1.3$. There was also a significant main effect of launch angle, $F(6,162) = 28.9$, $p < 0.001$, $\eta_p^2 = 0.52$. As can be seen in **Figure 3**, this occurred because coordination scores were higher for balls launched closer to the foul lines (i.e., larger angle) as opposed to those traveling up the middle. The group × launch angle was not significant, $p = 0.77$, $\eta_p^2 = 0.05$.

Figure 4 shows the mean decision times for the three groups plotted as a function of launch angle. The ANOVA performed on these data revealed significant main effects of group, $F(2,27) = 54.7$, $p < 0.001$, $\eta_p^2 = 0.8$, and launch angle, $F(6,162) = 47.4$, $p < 0.001$, $\eta_p^2 = 0.63$. However, these

[1]The choice of which position should field the ball as judged by the coaches was identical to what would be derived by looking at which player was closest to the ball and considering typical player instruction. As shown in **Table 1**, for the −36, −12, 12 and 36° trajectories there was one fielder that had the smallest angular separation to the ball. In each of these situations, the coaches' choices matched the position with the smallest angle. For the −24, 0 and 24° angles there were two players that were equidistant from the ball. The most common throw made by baseball infielders is to first base (1B). Thus, players are typically taught that in the situation where there are two infielders that could field the ball, the player whose momentum is going toward first base should field the ball. In terms of the values shown in **Table 1**, this means when both players have an equal angular separation to the ball, the player with the positive angle should field it. This again exactly matched the choices made by the coaches for the 24, 0 and −24° angles.

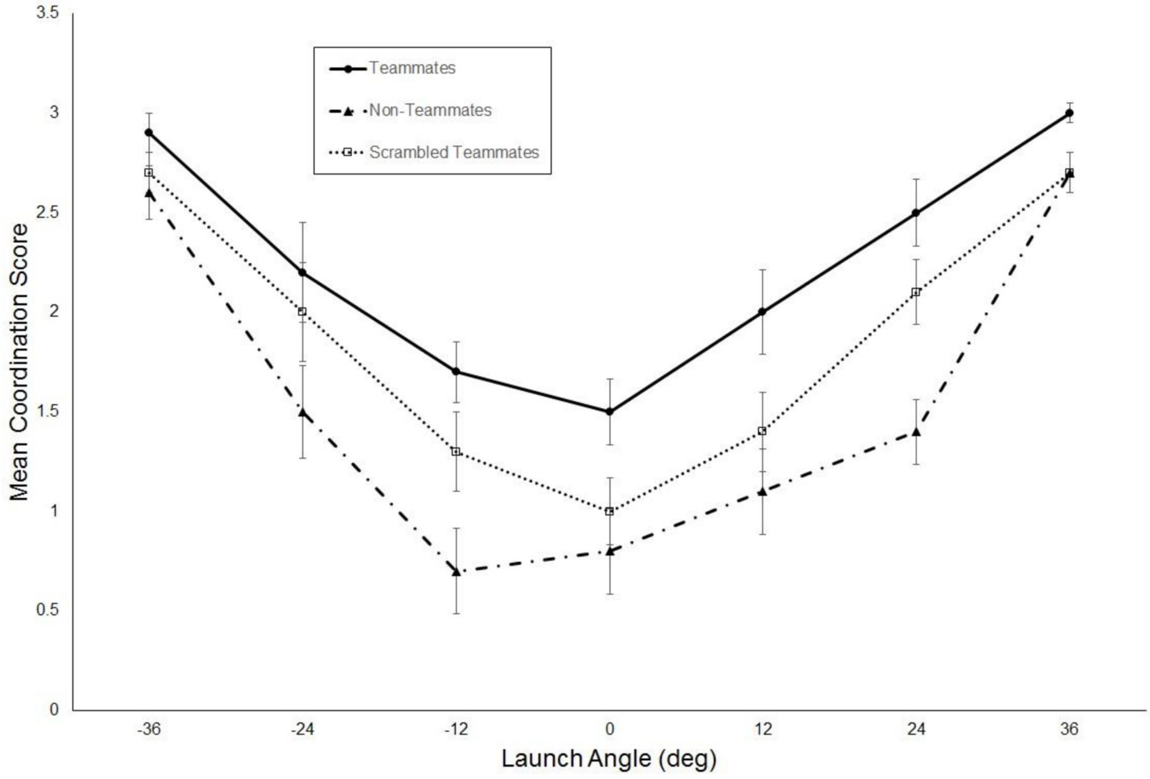

FIGURE 3 | Mean coordination scores plotted as a function of ball launch angle. Error bars are standard errors.

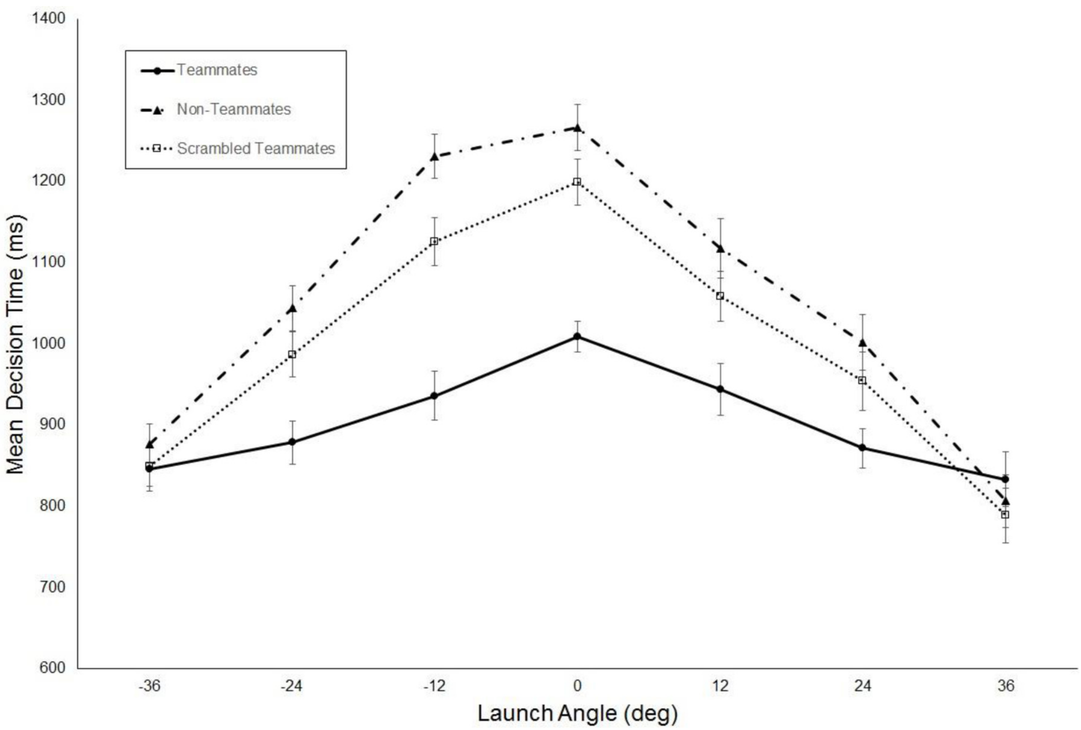

FIGURE 4 | Mean decision times plotted as a function of ball launch angle. Error bars are standard errors.

effects were qualified by a significant group × launch angle interaction, $F(12,162) = 3.6$, $p < 0.001$, $\eta_p^2 = 0.21$. As apparent in **Figure 4**, this interaction occurred because the differences in decision times between groups occurred for the smaller launch angles. Independent samples t-tests (with Bonferroni correction, $p = 0.006$) revealed that the decision time was significantly shorter for the teammates group as compared to the non-teammates for the 0° [$t(18) = 7.0$, $p < 0.001$, $d = 2.8$] 12° [$t(18) = 4.3$, $p < 0.001$, $d = 5.6$] and −12° [$t(18) = 7.0$, $p < 0.001$, $d = 4.8$] launch angles. Similarly, the mean decision times were significantly shorter for the teammates group as compared to scrambled teammates group for the 0° [$t(18) = 4.7$, $p < 0.001$, $d = 3.8$], 12° [$t(18) = 3.1$, $p = 0.003$, $d = 1.7$], and −12° [$t(18) = 3.1$, $p = 0.003$, $d = 3.7$], launch angles. The decision time for the scrambled teammates group was significantly shorter than for the non-teammates for the 12° launch angle, $t(18) = 3.8$, $p = 0.001$, $d = 3.3$.

DISCUSSION

A novel, joint decision making paradigm was used to assess team cognition in baseball infielders. Because it is assumed that team coordination is enhanced through experience performing together, a first requirement of any new methodology is that it shows sensitivity to team experience. This was indeed the case in the present study as players who currently played on the same team (the teammates group) made more coordinated decisions about how to react to a hit ball than players from different teams (the non-teammates group). For balls hit near the middle of the field, the teammates group also made significantly faster decisions. The differences between these groups suggest that coordination in this situation is not achieved through a generic knowledge of how to play a particular position. Instead, we propose that it is due to the fact that the teammates possess both knowledge about how their teammates will respond to particular game situations and knowledge about their teammates action capabilities (e.g., their lateral speed or "range"). This appears to be knowledge that a randomly grouped selection of non-teammates does not have. It is also important to note that our paradigm eliminated some possible explanations for why this effect might be seen if only player movements were examined. Specifically, our joint occlusion paradigm removed the ability to use any verbal or non-verbal communication and prevented players from seeing how their teammates reacted before making their own decision.

An unexpected finding of the present study, that was inconsistent with our second hypothesis, was that teammates "playing out of position" (the scrambled teammates group), made quicker (for balls with small launch angles) and more coordinated decisions than non-teammates viewing the videos from their typical playing position. This suggests that knowledge about the action capabilities of one's teammates is more important for team coordination than knowledge about how to play one's position at an individual level. These results are consistent with the idea that joint action in sport involves perceiving both one's own affordances for action and those of one's teammates (Fajen et al., 2008).

This team-based occlusion paradigm successfully distinguished three team configurations and different levels of game difficulty. Within the baseball infielder context used in present study, there are several interesting questions that could be addressed with this paradigm in future studies. First, the occlusion time could be systematically manipulated to investigate when decisions are made as has been used for individual decisions in sport (e.g., Abernethy and Russell, 1984). Second, the camera/player positions could be varied from trial to trial to determine how players take into account their relative starting positions in making their decisions. Finally, it would be interesting to use this team-based occlusion method to assess how players respond to the infield shifts (e.g., moving the first baseman, second baseman and shortstop all on the right side of the infield) that are becoming increasingly common in baseball (Los Angeles Times, 2015). Note, the scrambled teammates condition used in the present study was purposely designed to be different than the typical shifts made by infielders. Future work should also extend this paradigm to other team domains in which rapid decisions are needed for coordinated action (e.g., fire-fighting, special forces, and paramedics). Finally, other team configurations can be tested, as well as interventions predicted to improve team coordination (e.g., coaching, simulation training).

The methodology used in the present study deliberately simplified the task of making decisions in a baseball infield by restricting the information available to players to only the flight of the ball. It will be important for future research to add in other sources of information that are available in a real game. First, players should be allowed to communicate with each other, both verbally or non-verbally. Yelling "I got it" or "mine" is an essential part of baseball that players are taught from an early age (Delmonico, 1996). Furthermore, non-verbal communication (e.g., pointing or waving) is also commonly used in baseball (Delmonico, 1996) and has been shown to be critical for team coordination in other sports (e.g., LeCouteur and Feo, 2011). A second limitation of the current paradigm that should be addressed in the future is that the views seen by the players were static and were not yoked to their own head and body movements. This is important because actively exploring the environment can create additional perceptual information (e.g., head movements provide motion parallax information about the relative depth of objects) and experienced performers do seem to use this general strategy (e.g., Huet et al., 2011). One possible way of adding both of these information sources would be to use a virtual reality simulation of infield scenarios in which each a player's view is yoked to their head movement and players can communicate via a headsets like in a multiplayer video game.

AUTHOR CONTRIBUTIONS

All authors listed, have made substantial, direct and intellectual contribution to the work, and approved it for publication.

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Two Trackers Are Better than One: Information about the Co-actor's Actions and Performance Scores Contribute to the Collective Benefit in a Joint Visuospatial Task

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When humans collaborate, they often distribute task demands in order to reach a higher performance compared to performing the same task alone (i.e., a collective benefit). Here, we tested to what extent receiving information about the actions of a co-actor, performance scores, or receiving both types of information impacts the collective benefit in a collaborative multiple object tracking task. In a between-subject design, pairs of individuals jointly tracked a subset of target objects among several moving distractor objects on a computer screen for a 100 trials. At the end of a trial, pairs received performance scores (Experiment 1), information about their partner's target selections (Experiment 2), or both types of information (Experiment 3). In all experiments, the performance of the pair exceeded the individual performances and the simulated performance of two independent individuals combined. Initially, when receiving both types of information (Experiment 3), pairs achieved the highest performance and divided task demands most efficiently compared to the other two experiments. Over time, performances and the ability to divide task demands for pairs receiving a single type of information converged with those receiving both, suggesting that pairs' coordination strategies become equally effective over time across experiments. However, pairs' performances never reached a theoretical limit of performance in all experiments. For distributing task demands, members of a pair predominantly used a left-right division of labor strategy (i.e., the leftmost targets were tracked by one co-actor while the rightmost targets were tracked by the other co-actor). Overall, findings of the present study suggest that receiving information about actions of a co-actor, performance scores, or receiving both enables pairs to devise effective division of labor strategies in a collaborative visuospatial task. However, when pairs had both types of information available, the formation of division of labor strategies was facilitated, indicating that pairs benefited the most from having both types of information available (i.e., actions about the co-actor and performance scores). Findings are applicable to circumstances in which humans need to perform collaborative visuospatial tasks that are time-critical and/or only allow a very limited exchange of information between co-actors.

Keywords: Social cognition, visuospatial attention, collective benefit, joint action, Multiple object tracking

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1. INTRODUCTION

In everyday life, humans often perform tasks collaboratively that otherwise would be too difficult or cumbersome to perform alone. In such joint tasks, humans coordinate their actions in space and time in order to achieve a shared goal (i.e., a change in the environment; for general reviews, see: Sebanz et al., 2006; Frith and Frith, 2012; Vesper et al., 2016a). For instance, when two people are searching for a friend in a large crowd, one person may focus his search on the left half of a crowd while the other person searches the right half of the crowd (Brennan et al., 2008). Such a distribution of task demands between co-actors enables groups to reach a higher performance than their individual performances (i.e., a collective benefit) (Brennan et al., 2008; Bahrami et al., 2010).

Collective benefits have been researched extensively in the past in several domains such as decision-making (Bahrami et al., 2010, 2012a,b), attention (Brennan et al., 2008; Neider et al., 2010; Wahn et al., 2016c; Brennan and Enns, 2015), or sensorimotor processing (Knoblich and Jordan, 2003; Masumoto and Inui, 2013; Ganesh et al., 2014; Rigoli et al., 2015; Skewes et al., 2015; Wahn et al., 2016b). This work has converged on the conclusion that several factors may influence if, and to what extent, groups outperform individuals (Knoblich and Jordan, 2003; Brennan et al., 2008; Bahrami et al., 2010).

One of these factors is the type of information that is exchanged between co-actors (Brennan et al., 2008; Neider et al., 2010; Wahn et al., 2016c). For instance, in a study by Brennan et al. (2008), the type of exchanged information systematically affected collective benefits in a collaborative visual search task. In particular, in their study, participants performed a search task either alone or in pairs. While they searched together, they were either not permitted to communicate or they were allowed to communicate in one of three ways: verbally, by seeing a cursor on the screen indicating where their search partner was looking, or both, verbally and by seeing the cursor. While Brennan et al. (2008) generally found that pairs outperformed individuals, the most efficient search performance was achieved when pairs only received their partner's gaze information (i.e., information where their search partner was looking). In this condition, pairs effectively divided the search space into two parts that only minimally overlapped, enabling them to require only half of the time individuals needed to complete the search. These findings generally suggest that the collective benefit in visuospatial tasks such as collaborative visual search depends on an effective exchange of information about the performed actions of co-actors. In this particular case, it is an effective exchange of gaze information that enables co-actors to efficiently perform the collaborative visual search task. However, there are questions related to collaborative visuospatial tasks that have not been investigated, yet. Specifically, it has not been investigated to what extent receiving information about the performance accuracy (e.g., whether trials were correctly classified as target present or not present in a joint visual search task) contributes to the collective benefit, as this aspect of the task was not manipulated experimentally in earlier studies (Brennan et al., 2008; Neider et al., 2010; Wahn et al., 2016c). Additionally, it has not been investigated to what extent exchanging information about the co-actors' actions by itself contributes to the collective benefit.

While the contribution of the performance accuracy to the collective benefit has not been researched in collaborative visuospatial tasks, its contribution has been investigated in the domain of collaborative decision-making (Bahrami et al., 2010, 2012a). In particular, researchers investigated to what extent receiving performance scores, verbal communication, or both (i.e., performance scores as well as verbal communication) can predict a collective benefit in a collaborative visual discrimination task (Bahrami et al., 2010, 2012a). Results showed that participants reached the highest collective benefit when they were allowed to communicate and received performance scores. They still reached a collective benefit when they were only allowed to communicate with each other but when only performance scores were provided, no collective benefit was achieved. Notably, an analysis of the verbal communication showed that pairs who were linguistically aligned (i.e., used similar linguistic practices) showed a greater collective benefit (Fusaroli et al., 2012; Fusaroli and Tylén, 2016). In sum, pairs in a collaborative decision-making task can reach a collective benefit when they verbally negotiate their joint decisions. Importantly, this collective benefit is further increased when also having performance scores available, suggesting that performance scores in combination with other information can facilitate reaching a collective benefit.

Taken together, previous studies investigating collective benefits in collaborative visuospatial tasks showed that exchanging information about the co-actors' performed actions leads to a high collective benefit (Brennan et al., 2008; Neider et al., 2010; Brennan and Enns, 2015; Wahn et al., 2016c). Other studies investigating collective benefits in a collaborative decision-making task showed that having performance scores available about the individual and co-actors' decisions can further increase an already existing collective benefit (Bahrami et al., 2010, 2012a). To date, however, researchers have not investigated to what extent receiving information about the co-actor's performed actions, receiving performance scores, or both contributes to the collective benefit in a collaborative visuospatial task.

In the present study, three experiments tested how information on the performed actions of a co-actor, performance feedback, or both, contribute to the collective benefit in a multiple object tracking ("MOT") task (Pylyshyn and Storm, 1988) that is performed together. As a point of note, human performance in a MOT task has predominantly been studied in isolation (Cavanagh and Alvarez, 2005; Alvarez and Franconeri, 2007; Wahn and König, 2015a,b; Wahn et al., 2016a, 2017). To the best of our knowledge, the present study is the first to investigate collaborative behavior of two individuals in a jointly performed MOT task. In a MOT task that is performed alone, participants first see several stationary objects on a computer screen and a subset of these objects are indicated as "targets." Then, objects become indistinguishable and move across the screen in random directions for several seconds and participants are instructed to track the movements of the targets. When objects stop moving, participants are required to select which objects were the targets and then typically receive information about their performance (i.e., whether objects were correctly selected or not). We chose the MOT task for the present study as it allows a quantification of performance scores (i.e., correctly selected objects). In addition, the exchange of information about the actions of co-actors (i.e., the selected objects) can be precisely controlled. Moreover, the MOT task is a highly demanding visuospatial task if it is performed by one individual (Alvarez and Franconeri, 2007; Wahn et al., 2016a), potentially motivating the need for co-actors to divide task demands. Finally, the MOT task does allow to divide task demands – for instance, one co-actor could decide to track one subset of targets while the other co-actor could decide to track the complementary set of targets.

In the collaborative version of the MOT task designed for the present study, two participants perform the MOT task at the same time. In particular, both participants receive the same target indications and see identical object movements on their individual computer displays. Once objects stop moving, members of a pair individually select the objects that they think are the targets. Then, in Experiment 1, pairs receive performance scores that are composed of the individual tracking performance scores and the pairs' total performance score (Experiment 1). That is, members of a pair receive feedback on how well they performed individually (i.e., whether their target selections were correct or not) and also how well they performed jointly as a pair (i.e., whether the pair's combined target selections were correct or not). In Experiment 2, pairs receive information about which objects were selected by their co-actor but no performance scores. In Experiment 3, both, performance scores (i.e., both individual and pair performance scores) and information about the partner's selections are available to the pairs.

We hypothesized that all types of provided information would separately and in combination lead to collective benefits. That is, a pair should reach a higher performance than either of the individuals constituting the pair. In particular, given earlier research on collective decision-making (Bahrami et al., 2010, 2012a), we hypothesized that having performance scores about the individual and pair's performance (Experiment 1) enables members of a pair to adjust their behavior on a trial-by-trial to devise an effective collaborative strategy. In line with earlier findings on collaborative visual search (Brennan et al., 2008; Neider et al., 2010; Brennan and Enns, 2015; Wahn et al., 2016c), when having information about the partner's object selections available (i.e., information about the actions of a co-actor – Experiment 2), we hypothesized that pairs would reach a collective benefit as well. That is, we expected that co-actors can effectively distribute the number of targets that co-actors were required to track. When having both kinds of information available (Experiment 3), we predict that this would lead to the largest collective benefit as pairs can effectively distribute the number of targets and can also use the performance scores to verify whether their division of labor strategies are effective, further enhancing the collective benefit (Bahrami et al., 2010, 2012a).

2. METHODS

2.1. Participants

A total of 96 students (66 female) were recruited as participants at the University of Osnabrück and the University of British Columbia. Participants were evenly distributed across the three experiments. For each experiment, 32 students were grouped in 16 pairs (Experiment 1: $M = 24.19$ years, $SD = 4.73$; Experiment 2: $M = 21.13$ years, $SD = 2.85$ years; Experiment 3: $M = 22.53$ years, $SD = 3.88$ years). Experiments 1 and 3 were conducted at the University of Osnabrück while Experiment 2 was conducted at the University of British Columbia. Participants either received course credits or a monetary compensation for their participation. All participants had normal or corrected to normal vision. The study was approved by the ethics committee of the University of Osnabrück and of the University of British Columbia. Written informed consent was obtained from each participant.

2.2. Experimental Setup

Each member of a pair was seated at a 90 cm distance in front of a computer that was concealed from the other member's computer either by a curtain or an occluder. Stimulus parameters for the multiple object tracking task (see Experimental Procedure below), screen resolution (1920×1000) and screen sizes (24′) were matched for the setups of all experiments. In order to minimize external noise, participants wore ear muffs throughout the whole experiment.

2.3. Experimental Procedure

Pairs were first verbally instructed about the experimental procedure and then one example trial was shown by the experimenter to illustrate the experimental procedure. In an experimental trial, participants first saw 19 stationary white objects (0.56 visual degree radius) for 2 s located in randomly chosen positions on the computer screen (see **Figure 1A**). Then, always six of these objects turned gray for 2 s (referred to as "targets," see **Figure 1B**). Objects then turned white again and after an additional 0.5 s started to move in random directions across the screen for 11 s (see **Figure 1C**). Participants were instructed to track the movements of the targets. The object's velocity was randomly assigned to each object, varying between 0.90 and 1.21 visual degrees per second. While objects were moving, if they met the screen border or if their paths intersected they would "bounce" in a physically plausible way (i.e., angle of incidence equaled the angle of reflection). After objects stopped moving, both members selected the objects they thought were the targets. They indicated their decisions using a computer mouse (see **Figure 1D**).

Participants were allowed to select as many objects as they wanted. They were instructed that correctly selected target objects would add one point to their individual performance, whereas one point would be subtracted for each incorrectly selected object. Participants were also instructed that correct overlapping selections (i.e., when the same object was selected by both members of a pair) would add only one point to the pair's performance. Similarly, only one point would be subtracted

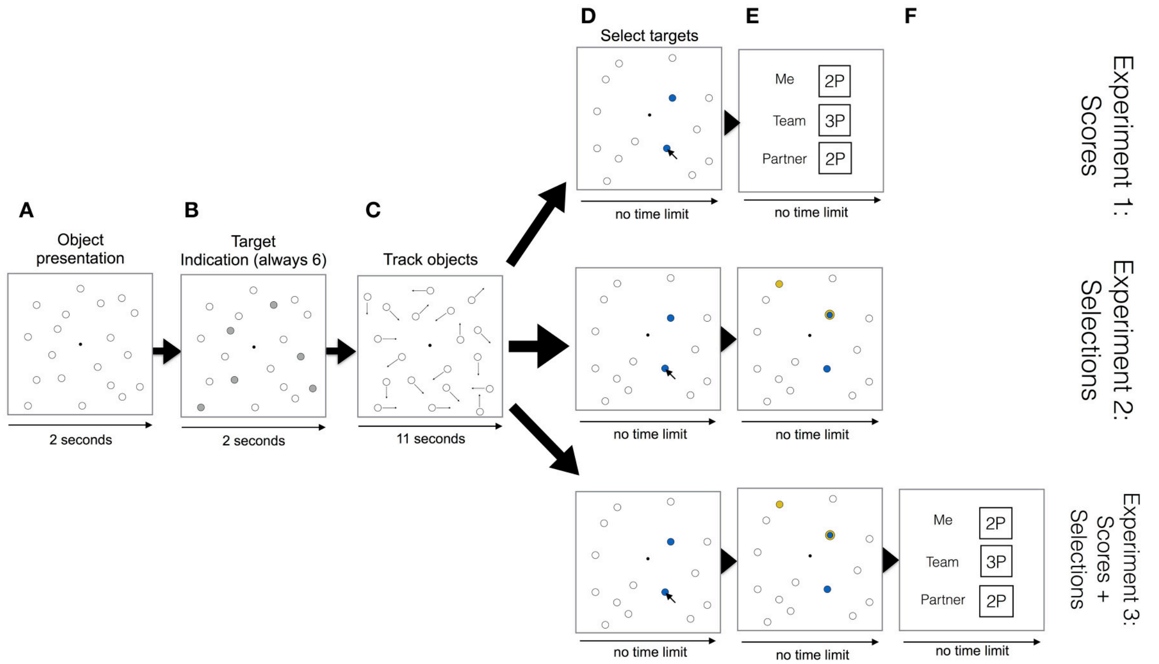

FIGURE 1 | Trial overview. (A) Object presentation: 19 stationary white objects are presented. **(B)** Target indication: A subset of 6 targets are indicated in gray. **(C)** Track objects: Objects move across the screen bouncing off each other and from the screen borders. **(D)** Select targets: Participants individually select objects that they think are the targets. **(E)** First row: Participants receive scores about their individual performances (i.e., "Me" and "Partner") and the pair's performance ("Team"). Second and third row: In addition to the member's own selections (shown in blue), the partner's selections are also shown (in yellow). Overlapping selections are shown in both colors. **(F)** Third row: After participants receive information on the partner's selections (and possible overlapping selections), they receive scores about their individual performances and the pair's performance.

from the pair's performance in the case of incorrect overlapping selections. So, for example, as depicted in 1E (first row), both members would get 2 points as their individual scores (see "Me" and "Partner") for selecting 2 targets correctly, and as one of the correct selections overlaps, the pair's performance (see "Team") would be 3 points.

Pairs were instructed to collaborate with the goal being to maximize the number of scored points for the pair's performance. Note, pairs were not allowed to verbally communicate throughout the whole experiment. The information exchange between members of a pair was limited to the information they received in the MOT task. Participants logged in their responses by clicking on a central black dot (0.15 visual degree radius) on the computer screen with a computer mouse. Once both members of a pair logged in their responses, depending on the experiment, different types of information were received by the participants: In Experiment 1, participants received scores about their individual performances (i.e., "Me" and "Partner") and the pair's performance ("Team," see **Figure 1E**, 1st row). In Experiment 2, pairs received information about the target selections of the partner in addition to their own selections (see **Figure 1E**, 2nd row). In Experiment 3, both, the partner's selections and performance scores, were received in succession (see **Figure 1E,F**, 3rd row). For viewing each type of information (i.e., performance scores and partner's target selections), no time limit was imposed and participants could continue whenever they felt ready for the next trial by pressing the space key on the keyboard. Whenever one of the co-actors was finished earlier than the other co-actor, pressing the space key resulted in a blank white screen being shown, which signaled to the participant to wait for their co-actor. Participants were instructed that pressing the space bar indicated that they were ready to proceed with the next trial. Once both participants had indicated that they were ready to proceed, one of the members was prompted to start the next trial by pressing the space key on the keyboard.

The experiment lasted a total of 100 trials. After the trials were completed, participants filled out a questionnaire in which they indicated whether they used a strategy to collaborate with their partner or not. If they used a strategy, participants were asked to describe the strategy in detail and whether it changed over the course of the experiment. In Experiment 3, we also asked participants whether, for developing their strategy, they relied more on the information about the target selections or the performance scores.

The experiment was programmed using Python 2.7.3, and lasted about 1 h per pair.

2.4. Dependent Variables

For assessing whether pairs reached a collective benefit, we used several performance measures, derived measures, and theoretical limits.

First, we extracted three types of performance measures (referred to as "min,""max," and "pair") for each trial. For the min and max performance, we extracted the worst and best of the two individual performances based on how many points they received on a per trial level. The pair performance is the actual performance of the pairs.

We defined the collective benefit as the difference between the pair performance and the max performance. That is, in order to test for collective benefits, we compared the difference between the max performance with the pair performance later in the analysis.

In addition, based on the correct and incorrect selections of the members of a pair, we calculated a theoretical upper and lower limit for each of the pairs' performances in a trial taking into account the individual performances. In particular, for the upper limit, we assumed that the members' correctly identified targets to be non-overlapping selections. The reasons for this choice is that, as pointed out above, a correctly selected target that both members of a pair select would add only one point to the pair's performance while two correctly selected targets that are non-overlapping would add two points to performance. Hence, treating correct target selections as non-overlapping selections maximizes the pair's performance. For incorrect target selections, we assumed that the members' selections should be overlapping selections as an incorrect overlapping selection leads to a reduction of the pair's performance by only one point compared to two points when incorrect selections would be non-overlapping. Hence, treating incorrect target selections as overlapping selections minimizes reductions of the pair's performance. In sum, this procedure (i.e., assuming non-overlapping selections for correct selections and overlapping selections for incorrect selections) maximizes the number of points for correct selections and minimizes the reductions for incorrect selections, resulting in an upper limit of performance. For the lower limit, we reversed this pattern of how correct and incorrect selections were assigned (i.e., overlapping selections for correct selections; non-overlapping selections for incorrect selections). These measures allowed us to normalize the pairs' performance within each experiment to compare performances across experiments later on.

A recent study by Brennan and Enns (2015) suggests the need for another baseline for comparison. In their study, a lower bound to assess the independence of co-actors was computed for a collaborative visual search task (Brennan and Enns, 2015) using a race model (Miller, 1982). Brennan and Enns (2015) reasoned that having such a simulated lower bound of performance is a more appropriate lower bound than comparing performance to the individual performance of the better member of a pair (i.e., a lower bound used to assess collective benefits Bahrami et al., 2010). In particular, Brennan and Enns (2015) argued that a collective benefit can in principle be achieved with members of a pair acting independently simply due to the fact that two people perform a task. Therefore, we additionally estimated a pair performance based on the individual performances under the assumption that members of a pair act independently (termed "independent"). That is, the number of overlapping selections of individuals and whether these overlapping selections are correct or incorrect would randomly vary from trial to trial as participants would not intentionally select objects that systematically overlap or do not overlap. For the purpose of simulating the independent performance, for each trial of each pair, we took the hits and false alarms of each member and randomly distributed these among the targets and distractors. Based on these randomly distributed hits and false alarms, we computed a hypothetical pair performance. We repeated this procedure a 1000 times, resulting in a distribution of pair performances for a particular trial sampled under the assumption that members of a pair act independently. As an estimate of the independent performance for each trial and each pair, we took the mean of the simulated distribution of pair performances. By simulating such an additional lower bound of performance under the assumption that members of a pair act independently, the actual pairs' performances can be tested against this bound to assess whether members of a pair actually collaborated when they perform a task together (e.g., devise a collaborative strategy to distribute task demands).

As a point of note, the lower limit, upper limit, and independent performance are based entirely on the individual performances of members of a pair and not on the pairs' performances.

As a measure of how well co-actors divided task demands, we calculated the overlap for the target selections (i.e., how many object selections of members of a pair overlap) for each trial and divided this measure by the total number of selections.

2.5. Sliding Window

To analyze our dependent variables across time, we performed a sliding window for each pair. In particular, as a first window, we took the data from the first ten trials of the experiment and calculated the mean across these trials and replaced the value of the first trial by that mean. We then shifted this window always by one trial (e.g., for the next step, we would use trials two to eleven) and repeated this procedure up to the 91st trial.

2.6. Cluster Permutation Tests

In order to assess whether performances differed significantly across time and between experiments, we used cluster permutation tests (Maris and Oostenveld, 2007). That is, given that we are interested in *when* pairs' performances reach a collective benefit, surpass the independent lower bound of performance, and differ between experiments, comparisons between conditions for each trial would be required. However, such a high number of comparisons would result in a high number of false positives, requiring the need to correct for multiple comparisons. Cluster permutation tests circumvent the need to correct for multiple comparisons as they take into account the relation between adjacent time points (i.e., trials in the present study) and statistical tests are performed on clusters (i.e., adjacent time points that exceed a critical value are grouped in one cluster) (Maris and Oostenveld, 2007). For a cluster permutation test, we first calculated the maximum number of temporally adjacent trials for which t-values with the same sign exceeded the critical t-value of significance. This maximum number constituted the largest cluster in the data. We also repeated this procedure to find the second largest cluster. As a point of note, for computing the t-values, if the comparison was a within-subject comparison (e.g., comparing the pairs' performances to the independent condition), we used the formula of a dependent t-test. For between-subject comparisons (e.g., comparisons across experiments), we used the formula for an independent t-test to compute the t-values. Finally, for comparisons of the pairs' data with a constant, we used a one sample t-test.

In order to assess the probability of cluster sizes occurring by chance, we simulated a hypothetical null distribution of cluster sizes under the assumption that there are no differences between the compared conditions. In particular, for within-subject comparisons, we randomly reassigned condition labels within each pair (e.g., whether the data belongs to the "independent" or "pair" condition) and calculated the largest cluster in this randomized data using the approach outlined above (i.e., grouping temporally adjacent trials in a cluster for which t-values with the same sign reach significance). For a between-subject design involving comparisons across experiments, we randomly assigned pairs to the experiments that are compared. For comparisons of the pairs' data with a constant, we randomly assigned condition labels (i.e., "constant" or "pair") within each pair. This procedure was repeated a 1,000 times with each iteration yielding the largest cluster in the randomized data. As a result, we created a null distribution of cluster sizes that was sampled under the assumption that there are no differences between the compared conditions.

To evaluate the significance of the largest cluster and the second largest cluster in the actual data, the p-values of these clusters were computed by calculating the fraction of clusters in the null distribution that were larger than the largest and second largest cluster in the actual data, respectively. If this fraction was below 0.05, a cluster in the actual data was deemed significant.

For all comparisons using a cluster permutation test, we report the extent of a cluster (range of trials), the p-value, and as an effect size Cohen's d averaged over the trials within a cluster (i.e., for each trial comparison, a separate Cohen's d is calculated). We chose Cohen's d as an effect size measure as it provides a normalized measure of the effect (i.e., standard deviation units) without taking the sample size into account. Note, depending on the type of comparison (i.e., whether it is a within-subject or between-subject comparison, or comparison with a constant), we used the appropriate numerator and denominator for the Cohen's d calculation. For a within-subject comparison, we used the standard deviation of the differences. For a between-subject comparison, we used the pooled standard deviation and for a comparison with a constant, we used the standard deviation of the group that is compared with the constant.

As a point of note, the extent of the clusters will not be interpreted in an absolute sense (Maris and Oostenveld, 2007). That is, we do not interpret the extent of a cluster within an experiment as the cluster sizes are dependent on several pre-selected factors (e.g., chosen critical value for the t-statistic, number of trials, number of participants). The extent of clusters within each experiment will only be interpreted in relation to the extent of clusters in the other experiments as the pre-selected factors influencing the cluster sizes are kept constant across experiments.

3. RESULTS

In order to assess whether pairs reached a collective benefit and to what extent it differed across experiments, we first analyzed the pairs' and individuals' performances in each experiment and across experiments (see subsection "Collective Benefits" below). For assessing how effectively members of a pair divided task demands depending on the available information and their strategy-use, we then investigated the pairs' target selections and to what extent these overlap. Moreover, we assessed which type of division of labor strategies participants described in the questionnaire on strategy-use and whether the description fits to what participants did in the experiments (see subsection "Task Division & Strategy-use" below).

3.1. Collective Benefits

For each experiment, we analyzed whether the pairs' performances reached a collective benefit and also exceeded the estimated independent performance (i.e., a higher pair performance than max and independent; for a descriptive overview, see **Figures 2A–C**) using cluster permutation tests (for more details, see subsection "Cluster Permutation Tests" above). When pairs only received the performance scores (Experiment 1), pairs reached a collective benefit early (trials 3-91, $p < 0.001$, Cohen's $d = 1.43$) and over time exceeded the independent performance (trials 35–91, $p < 0.001$, Cohen's $d = 0.86$). We found similar results for the other two experiments. In particular, when pairs received only the partner's selections (Experiment 2), pairs also reached a collective benefit early (trials 2–91, $p < 0.001$, Cohen's $d = 1.30$) and exceeded the independent performance over time (trials 56–91, $p = 0.003$, Cohen's $d = 0.88$). In Experiment 3 (see **Figure 2C**), pairs received both the information of Experiments 1 and 2, they also reached a collective benefit early (trials 1–91, $p < 0.001$, Cohen's $d = 1.23$) and exceeded the independent performance (trials 16–91, $p = 0.01$, Cohen's $d = 1.20$). In sum, in each experiment, pairs reached a collective benefit and also exceeded the estimated independent performance. Comparing the extent of clusters across experiments, the collective benefit was reached early in each experiment while the pairs' performances exceeded the independent performance earlier in Experiment 3 than in Experiment 1 and 2 (see extent of significant clusters as gray areas in **Figures 2A–C**).

We also investigated in which experiment the pairs' performances stabilized the quickest (i.e., pairs did not improve their performance any further). For this purpose, we compared the pairs' performances in the last trial with the pairs' performances in the preceding trials using cluster permutation tests. For Experiment 1 ("Scores"), we found an early cluster (trials: 1–37, $p = 0.001$, Cohen's $d = 0.87$) and for Experiment 2 ("Selections") we also found an early cluster (trials 1-17, $p = 0.009$, Cohen's $d = 0.76$) as well as a later cluster (trials 43–52, $p = 0.033$, Cohen's $d = 0.75$). For Experiment 3 ("Selections+Scores"), we found that pairs' performances significantly differed from the

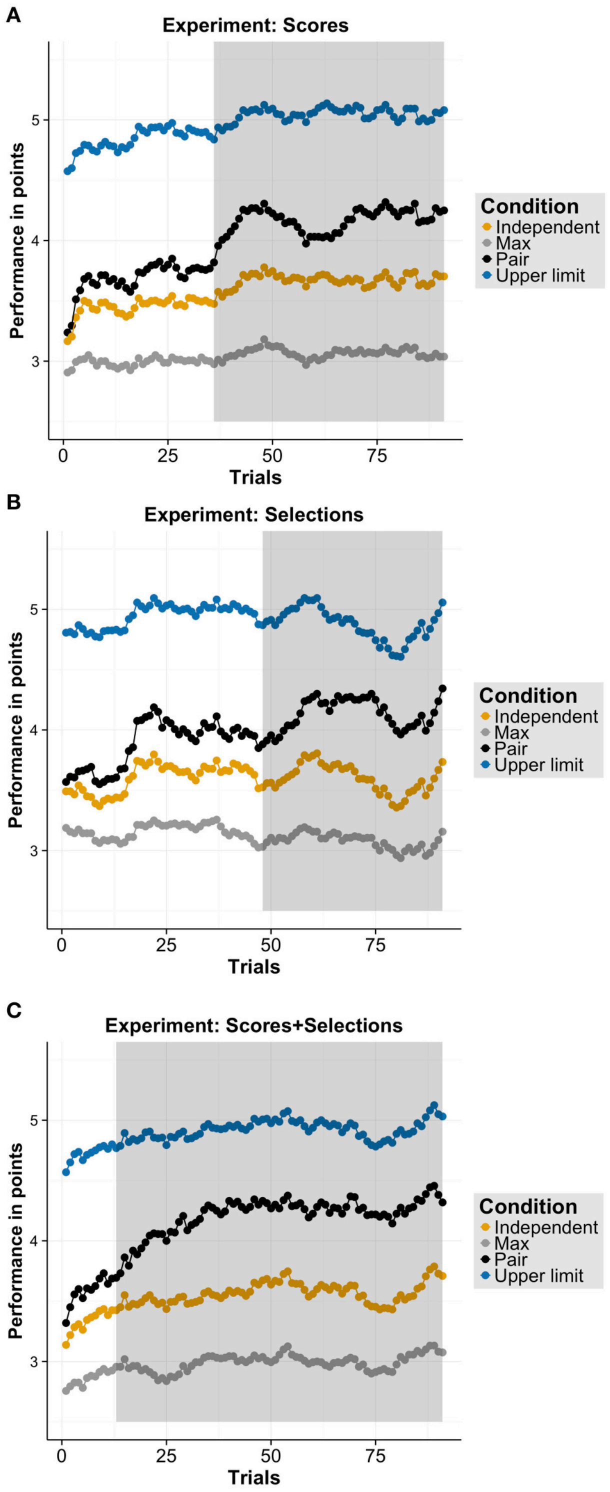

FIGURE 2 | Results overview. (A–C) Performance in points for each measure (i.e., "Independent," "Max," "Pair," "Upper limit"), separately for each Experiment: **(A)** Scores (Experiment 1), **(B)** Selections (Experiment 2), and **(C)** Selection+Scores (Experiment 3). Shaded regions indicate significant clusters using cluster permutation tests for comparing the pair's performance with the independent performance.

last trial in an early cluster (trials: 1–19, $p = 0.009$, Cohen's $d = 0.79$). Overall, the extent of the cluster in each experiment suggests that pairs' performances stabilized the quickest in Experiment 3 followed by Experiment 1 and 2.

In order to investigate which type of information provided in the experiments led to the highest pair performances, we compared for which trials the pairs' performances across experiments differed. In order to account for systematic differences between experiments due to different levels of individual performances, we normalized the pairs' performances in each experiment relative to the independent condition and the upper limit of performance (for a descriptive overview, see **Figure 3A**). On a descriptive level, pairs that received both types of information (Experiment 3) reached a higher performance earlier than pairs in the other two experiments. However, over time, the pairs' performances converged to similar levels of performance. We tested whether these observations are statistically reliable using cluster permutation tests. When comparing Experiment 1 with 2 or 3, we found no significant cluster. When comparing Experiment 3 with 2, we found a significant difference with a larger extent (trials: 35–52, $p = 0.030$, Cohen's $d = 0.24$). In sum, these comparisons suggest that pairs reached a higher performance in Experiment 3 than in Experiment 2. However, this performance advantage in Experiment 3 was not sustained over the course of the experiment as no significant clusters were found for later trials. In order to investigate this observation in more detail, we additionally tested with a one factorial between-subject ANOVA whether the pairs' peak performances differed across experiments (see **Figure 3B** for a descriptive overview). We found no significant difference between performances [$F_{(2, 45)} = 0.57$, $p = 0.570$]. These data suggest that pair's performances' converged to similar levels later in an experimental session.

Overall, we found that pairs in all experiments reached a collective benefit and exceeded the estimated independent performance when performing the MOT task together. Moreover, we found that pairs' performances stabilized earlier when receiving both types of information (i.e., scores and the partner's selections, Experiment 3) than when only receiving the scores (Experiment 1) or the partner's selections (Experiment 2). Pairs also reached a higher performance in Experiment 3 than in Experiment 2 at first. However this performance advantage was not sustained over time. That is, performances converged to similar levels toward the end of the experiment.

3.2. Task Division & Strategy-use

In order to assess how effectively members of pairs divided the task demands, we investigated the fraction of overlapping selections (i.e., number of overlapping selections divided by the total number of selections) across experiments (see **Figure 4A**). Analogous to the comparisons above involving the pairs' performances across experiments, on a descriptive level, the fraction of overlapping selections are reduced early on in Experiment 3 and gradually in Experiment 1 and 2, converging to similar levels later in the experiments. We compared the fraction of overlapping selections across experiments using

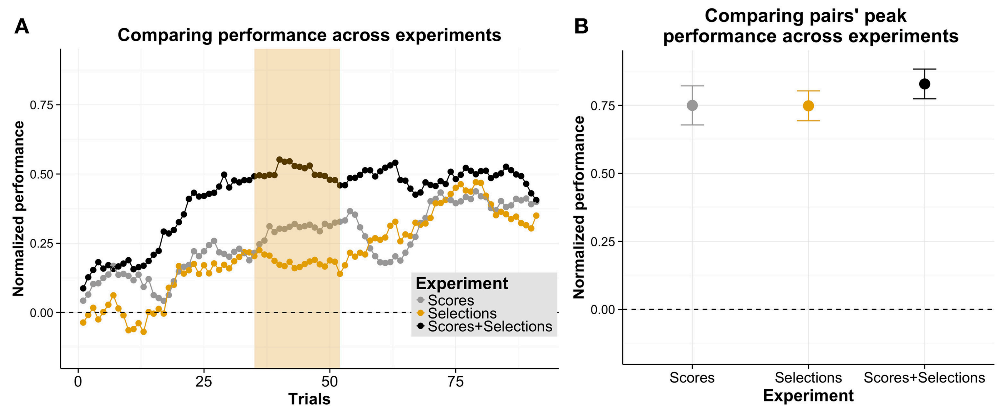

FIGURE 3 | Comparison of experiments. (A) Normalized performance as a function of trials, separately for each of the three experiments (Experiment 1 "Scores"; Experiment 2 "Selections"; Experiment 3 "Scores + Selections"). Pairs' performances are normalized relative to the independent and the upper limit performances. The yellow shading indicates significant comparisons between Experiment 3 and 2. **(B)** Mean peak performance of each pair as a function of experiment. The error bars are standard error of the mean.

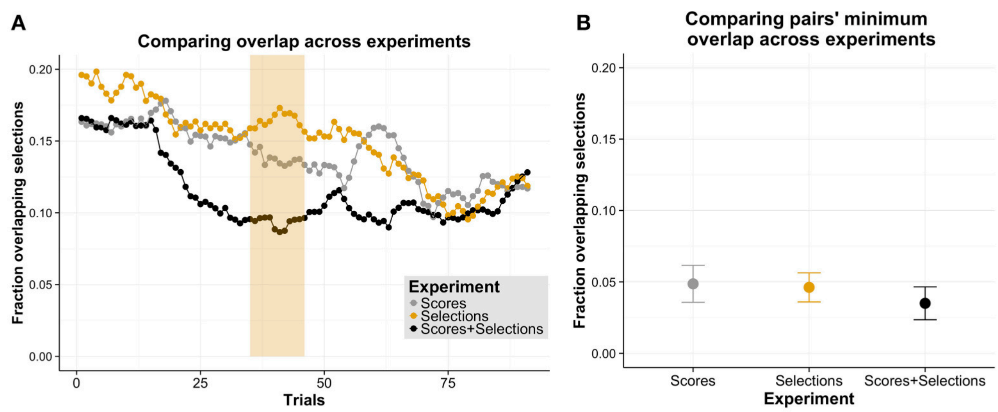

FIGURE 4 | Comparison of overlapping selections across experiments. (A) Fraction of overlapping selections as a function of trials, separately for each experiment (Experiment 1 "Scores"; Experiment 2 "Selections"; Experiment 3 "Scores + Selections"). The number of overlapping selections are normalized relative to the total number of selections. The yellow shading in panel **(A)** indicates significant comparisons between Experiment 3 and 2. **(B)** Mean minimal fraction of overlapping selections as a function of experiments. The error bars are standard error of the mean.

cluster permutation tests. We found no significant cluster when comparing Experiment 1 with Experiment 2 or 3. When comparing Experiment 3 with 2, we found a significant difference for a cluster with a larger extent (trials: 35–46, $p = 0.034$, Cohen's $d = 0.23$). These comparisons suggest that pairs reached a lower fraction of overlapping selections in Experiment 3 compared to Experiment 2. However, results also suggest that this difference is only present relatively early in the experiment as no significant clusters were found for later trials. In order to investigate this observation in more detail, we tested with a one factorial between-subject ANOVA whether the minimum fraction of overlapping selections of each pair differed across experiments (see **Figure 4B** for a descriptive overview). We found no significant difference for this measure [$F_{(2,45)} = 0.39$, $p = 0.678$], suggesting that pair's fraction of overlapping selections converged to similar levels.

In sum, when comparing the fraction of overlapping selections across experiments, similar to our analysis of the performance above, we found that pairs in Experiment 3 had a lower fraction of overlapping selections than in Experiment 2. However, this difference was not found in later trials and also not when comparing the minimum overlap for each pair.

In order to assess which type of strategies pairs used to divide task demands, we analyzed the participants' responses in the questionnaire about their strategy-use. We found that participants described either one of two types of strategies which we termed a "left-right" division of labor strategy and "outer-inner" division of labor strategy, or no strategy at all. For the left-right strategy, participants described that they divided the targets into the left-most and right-most portion at the start of a trial. For the outer-inner strategy, participants described that one of the participants tracked the targets that were located more in the center of the display at the start of a trial while the partner would track the targets that were further away from the center.

Analyzing the fractions of these responses, for Experiment 1, we found that participants were predominantly described a left-right strategy (53.125%), followed by the outer-inner strategy (25%), with the fewest (21.875%) describing no strategy at all. For Experiment 2, we found that participants would only either describe the left-right strategy (75%) or no strategy at all (25%). For Experiment 3, we found that a left-right strategy was described by the most (75%) followed by the outer-inner strategy (15.625%) and no strategy (9.375%). We tested whether these observed differences were statistically reliable using a 3×3 χ^2 test with the factors Strategy (left-right, outer-inner, none) and Experiment (Scores, Selections, Scores+Selections). We found a significant effect ($\chi^2 = 11.38$, $p = 0.023$), suggesting that the distribution of strategies differed across experiments, indicating that participants predominantly used a left-right strategy to collaborate with their partner. However, the use of a such a strategy was higher in the experiments in which the partner's selections were received (Experiments 2 and 3) than in an experiment in which only performance scores were received (Experiment 1).

In addition, we also compared the normalized performance between pairs that described a left-right strategy with pairs that either described an outer-inner strategy or no strategy in a 2 (Strategy) × 3 (Experiment) between-subject ANOVA. We found that pairs which described a left-right strategy performed significantly higher than pairs with an outer-inner strategy or no strategy [$M_{\text{left-right}} = 0.36$ vs. $M_{\text{other}} = 0.10$; $F_{(1, 42)} = 6.44$, $p = 0.015$]. We neither found a main effect of Experiment [$F_{(2, 42)} = 0.38$, $p = 0.176$] nor an interaction effect between the factors Strategy and Experiment [$F_{(2, 42)} = 0.352$, $p = 0.705$].

For Experiment 3, we additionally asked whether participants relied more on the partner's selections, scores, or both to develop their strategy. Participants indicated that they relied the most on the selections (50%) followed by scores (23.333%) and receiving both (26.666%). These results indicate half of the participants of Experiment 3 relied on the information about the actions of their co-actor to form strategies despite the fact that they have both types of information available.

Given such a high prevalence for a left-right division of labor strategy in the questionnaire data, we investigated whether pairs actually performed such a strategy. Given members of a pair used a left-right division of labor strategy, we reasoned that the initial object positions of members' own target selections should be closer together than the distance of target selections across members. For calculating this difference, we first calculated for each trial and each member of a pair the horizontal distance (in pixels) between the initial positions of their individually selected targets and averaged across these values for each trial – this measure will be referred to as "distance within." We then calculated the distance between the initial positions of the target selections *across* the selections of members of a pair ("distance across"). In order to have our final measure, we subtracted the distance across from the distance within values for each trial. As noted above, if members of a pair would use a left-right division of labor strategy, then we would expect a higher distance across value than distance within value, resulting in a negative residual. For this measure, on a descriptive level (see **Figure 5A** for an overview), we found a negative difference, suggesting that participants actually used a left-right division of labor strategy. We tested whether the calculated differences deviated significantly from zero using cluster permutation tests and found this to be the case for all experiments for clusters extending across all trials (Experiment 1: $p < .001$, Cohen's $d = 1.33$; Experiment 2: $p < 0.001$, Cohen's $d = 1.49$; Experiment 3: $p < 0.001$, Cohen's $d = 1.38$). These data converge on the conclusion that pairs actually applied a left-right division of labor strategy. We found no significant cluster permutation tests when we compared this measure across experiments ($ps \geq 0.24$).

In order to validate whether the chosen measure is an appropriate one to characterize division of labor strategies, we repeated the procedure above for the vertical distance instead of the horizontal distances (see **Figure 5B** for an overview). Here, a negative residual would indicate that participants tended to divide the targets along the vertical dimension (i.e., chose an "up-down" division of labor strategy). As participants did not indicate in the questionnaire to have divided task demands along the vertical dimension, we expected no systematic differences between "distance within" and "distance across" for

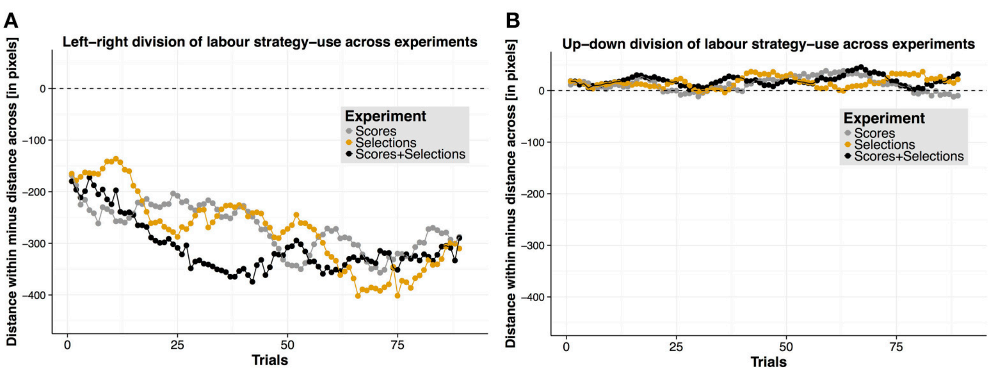

FIGURE 5 | Division of labor strategies. (A) Left-right division of labor strategy. Horizontal distance difference as a function of trials, separately for each experiment. **(B)** Up-down division of labor strategy. Vertical distance difference is shown as a function of trials, separately for each experiment.

each experiment. That is, systematic differences would only occur if the "distance within" and "distance across" measures were different regardless of whether participants used an "up-down" division of labor strategy or not. We found no significant cluster permutation tests within each experiment ($ps = 1$) and across experiments ($ps \geq 0.12$), suggesting that our measure to quantify left-right division of labor strategies, and the conclusion stemming from it, was valid.

4. DISCUSSION

In the present study, we investigated how receiving information about actions of a co-actor, performance scores, or both contribute to the collective benefit in a collaborative visuospatial task. In contrast to earlier studies that did not experimentally manipulate the availability of these two types of information (Brennan et al., 2008; Brennan and Enns, 2015; Wahn et al., 2016c), we systematically varied whether members of a pair received performance scores, only information about the actions of their co-actor, or both. We found that these types of information either alone or in combination enable pairs to achieve a collective benefit early on. Furthermore, in each experiment, pairs also surpassed the performance predicted if members of a pair acted independently, suggesting that pairs did indeed collaborate to improve their performance (i.e., they effectively divided task demands).

In addition, participants' subjective reports on strategy-use further corroborate the conclusion that members of a pair collaborated in the task, as the majority of participants reported to have used a division of labor strategy (i.e., either a left-right or outer-inner division of labor). The most prevalent strategy that was reported across experiments was a left-right division of labor strategy (i.e., one co-actor would always track the leftmost targets while the other co-actor the rightmost targets), and we objectively confirmed that pairs actually used such a strategy. Earlier studies on collaborative visual search also found that pairs devised spatial division of labor strategies as well (Brennan et al., 2008; Brennan and Enns, 2015; Wahn et al., 2016c). Our present findings suggest that co-actors in collaborative visuospatial tasks generally prefer to use left-right division of labor strategies. As another point of note, in the present study subjective reports of a left-right devision strategy were particularly prevalent when participants were provided with information about the co-actor's target selections, suggesting that information about the actions of co-actors especially foster the formation of a left-right division of labor strategy.

When comparing the performance across experiments, we found that pairs reached a significantly higher performance early on when receiving both performance scores and information pertaining to the partner's selections than when only receiving either the performance scores or the partner's selections. However, this performance advantage was not found for later trials, suggesting that the pairs' performances converged to similar levels over time. A comparison of the peak performances across experiments also revealed no significant difference across experiments. These results were further supported by a significantly lower fraction of overlapping selections early on when receiving both performance scores and the partner's selections in comparison to only receiving the partner's selections. In sum, these findings suggest that pairs that received both types of information devised an effective collaborative strategy early on that was not further improved in subsequent trials. In particular, we suspect that the effectiveness of devised strategies could be verified quickly using the available information on performance scores and the number of overlapping selections, enabling pairs to divide the task demands quickly and effectively.

When only information about the co-actor's actions was available, pairs could only use the information about the overlapping selections as a means to verify their strategies, possibly slowing down the formation of effective division of labor strategies. In particular, the information about the partner's selections only informs participants about the number of overlapping selections but does not inform them whether their selections were actually correct. However, the fact that pairs in this experiment ultimately devised equally effective strategies relative to the devised strategies in the other two experiments indicates that pairs' selections over time do become more accurate. More generally, if information about the actions of the partner is available to co-actors in a collaborative spatial task, findings suggest that performance scores are not strictly necessary to devise effective devision of labor strategies.

Conversely, when only performance scores were available, participants could only use the available performance scores to verify whether the effectiveness of their division of labor strategy is increasing or decreasing but do not have information available on the actions of their partner. Members of a pair can only hypothesize how the division of labor strategy is implemented (i.e., which targets are tracked by the partner). However, again, the fact that pairs' devised strategies were equally effective relative to the strategies devised in the other two experiments suggests that receiving information about the actions of the partner is not strictly necessary to devise effective division of labor strategies. In short, the findings suggest that performance scores about the individuals' performances and the pair's performance are sufficient to devise effective division of labor strategies in collaborative spatial tasks.

In sum, having either of the two types of information (i.e., the partner's selections or the performance scores) is sufficient to devise an effective division of labor strategy. Yet, having both types of information speeds up the development of such strategies.

Similar findings were found in earlier studies investigating collaborative decision-making tasks (Bahrami et al., 2012a). That is, pairs' performances were higher when they received performance scores in addition to exchanging information verbally compared to when they could only exchange information verbally without receiving any performance scores but converged to similar levels of performance over time (Bahrami et al., 2012a). Here, we found that in a collaborative visuospatial task, performance scores in addition to exchanging information about the co-actor's actions increased the pairs' performances at first and then converged to similar performance levels across experiments as well. More generally, these findings suggest that pairs in a collaborative task benefit from having an objective reference available to assess their performance.

Regarding division of labor strategies, a direction for future research is to identify the factors that may modulate the type of division of labor strategies that co-actors devise. For instance, the prevalence of left-right division of labor strategies could be biased by the shape of computer monitors that are used in studies investigating collaborative visuospatial tasks. In particular, monitors with a rectangle shape (i.e., with a larger width than height) were used in this study and earlier investigations on collaborative visuospatial tasks (Brennan et al., 2008; Brennan and Enns, 2015; Wahn et al., 2016c). For instance, it would be interesting to determine if left-right division of labor strategies vary in strength for quadratic stimulus displays and possibly flip to top-bottom strategies for rectangle displays with a greater height than width. More generally, traits as handedness (i.e., whether the participant is right or left handed) or the reading direction (i.e., whether the participant is a left-to-right or right-to-left reader) (Afsari et al., 2016) could also influence and/or facilitate the formation of strategies. That is, participants with opposite handedness' or reading directions may develop effective left-right strategies earlier.

Another possible direction for future studies could be to investigate whether division of labor strategies of similar effectiveness could be devised by decreasing the received information or replacing it by other information. Such studies would be of interest to investigate the minimal amount of information that needs to be exchanged between co-actors in a visuospatial task to devise effective division of labor strategies. In particular, in the present study the performance scores constituted feedback about the individual performances as well as the pair's overall performance. A future study could investigate the effectiveness of division of labor strategies when only a score about the pair's overall performance is available and no information about the individual performances is received. In particular, having no means to verify the accuracy of the individual selections might slow down the development of effective division of labor strategies and could modify the overall effectiveness of these strategies. Conversely, having only a score about the pair's performance available might be sufficient to devise an effective division of labor strategy, rendering individual performance scores unnecessary.

Another point to consider is that in the present study the information exchanged between co-actors of a pair was only given at the end of a trial. Future studies could investigate how the development of division of labor strategies is affected by exchanging information while simultaneously performing the collaborative MOT task. In particular, earlier studies on collaborative visual search tested to what extent the online exchange of spatial information about the actions of co-actors contributed to the collective benefit and found that this led to effective division of labor strategies (Brennan et al., 2008; Brennan and Enns, 2015; Wahn et al., 2016c). Similar to these studies, spatial information about the actions of co-actors (e.g., gaze information or verbal information) could be exchanged while participants track the objects in the MOT task. However, given findings of other studies investigating individual visuospatial processing capacities (Wahn and König, 2015a,b, 2016, 2017), processing spatial information about the actions of co-actors in addition to performing the MOT task could possibly interfere with performance, as both these types of information draw from a common pool of visuospatial attentional resources.

More generally, findings of the present study dovetail with other research that investigated the exchange of task-relevant information between co-actors in joint tasks (e.g., see: Knoblich and Jordan, 2003; Konvalinka et al., 2010, 2014; van der Wel et al., 2011; Fusaroli et al., 2012; Vesper et al., 2013, 2016b; Fusaroli and Tylén, 2016). That is, with regard to collective benefits, co-actors' joint performance is also facilitated by an exchange of information about the co-actors' task contributions in joint visuomotor tasks (Knoblich and Jordan, 2003; van der Wel et al., 2011) or in a joint perceptual decision-making task (Bahrami et al., 2010, 2012a; Fusaroli et al., 2012; Fusaroli and Tylén, 2016). Moreover, depending on the type of information that is exchanged between co-actors, co-actors systematically use different coordination mechanisms (Konvalinka et al., 2010, 2014; Vesper et al., 2016b). Relatedly, we find that the distribution of the used type of division of labor strategies changes depending on which type of information is exchanged between co-actors (i.e., information about the actions of co-actors, performance scores, or both).

From a more applied perspective, the present findings are applicable to circumstances in which humans need to perform demanding collaborative visuospatial tasks that are time-critical and/or only allow a very limited exchange of information between co-actors. Many professions place a high demand on visuospatial attention and at the same time require individuals to interact and cooperate. For instance, air-traffic controllers jointly need to track the trajectories of multiple airplanes on a screen. In such circumstances, it could be beneficial to only exchange the minimum amount of information necessary to devise an effective division of labor strategy, leaving more spare visuospatial attentional resources to perform the tracking task. Similarly, it would be beneficial for a security team tracking the position of several suspects in a large crowd to effectively divide task demands with only a minimum exchange of information, again leaving spare visuospatial attentional resources available to perform the tracking task more effectively. Moreover, the present findings are potentially applicable to scenarios, in which humans and robots jointly perform tasks (Schubö et al., 2007; Vesper, 2014; Ghadirzadeh et al., 2016). That is, the present study may provide indications which type of information is crucial for developing effective devision of labor strategies in collaborative visuospatial tasks that are jointly performed by humans and robots.

5. AUTHOR CONTRIBUTIONS

Study Design: BW, PK, and AK. Data Acquisition: BW. Data Analysis: BW. Wrote the manuscript: BW. Revised the manuscript: BW, PK, and AK.

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Network Characteristics of Successful Performance in Association Football. A Study on the UEFA Champions League

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The synergistic interaction between teammates in association football has properties that can be captured by Social Network Analysis (SNA). The analysis of networks formed by team players passing a ball in a match shows that team success is correlated with high network density and clustering coefficient, as well as with reduced network centralization. However, oversimplification needs to be avoided, as network metrics events associated with success should not be considered equally to those that are not. In the present study, we investigated whether network density, clustering coefficient and centralization can predict successful or unsuccessful team performance. We analyzed 12 games of the Group Stage of UEFA Champions League 2015/2016 Group C by using public records from TV broadcasts. Notational analyses were performed to categorize attacking sequences as successful or unsuccessful, and to collect data on the ball-passing networks. The network metrics were then computed. A hierarchical logistic-regression model was used to predict the successfulness of the offensive plays from network density, clustering coefficient and centralization, after controlling for the effect of total passes on successfulness of offensive plays. Results confirmed the independent effect of network metrics. Density, but not clustering coefficient or centralization, was a significant predictor of the successfulness of offensive plays. We found a negative relation between density and successfulness of offensive plays. However, reduced density was associated with a higher number of offensive plays, albeit mostly unsuccessful. Conversely, high density was associated with a lower number of successful offensive plays (SOPs), but also with overall fewer offensive plays and "ball possession losses" before the attacking team entered the finishing zone. Independent SNA of team performance is important to minimize the limitations of oversimplifying effective team synergies.

Keywords: Social Network Analysis, team sports, elite soccer, match analysis, expert performance, team synergy

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INTRODUCTION

The team, rather than the individual, has become the basic work unit in many activities and organizations (Balkundi and Harrison, 2006), and team sports are excellent examples revealing the importance of team dynamics for success (Duch et al., 2010). A team is a group of individuals working cooperatively and in a coordinated way to achieve a common goal (Zaccaro et al., 2002). Team performance is more than the sum of the interdependent individual performances, as individuals strive to coordinate between different roles and tasks (Anderson and Franks, 2001).

In team sports performance, individual players in a successful team act as a coherent unit, thus creating a team synergy (Araújo and Davids, 2016).

Individual and collective behavior has been intensively studied in team sports performance analysis. The behavior of an individual player affects the team's behavioral pattern (Vilar et al., 2012), and conversely, the teammates may influence the behavior of each individual player. Team behavior is a collective organization that emerges from the cooperation between teammates (Gréhaigne et al., 1997; Peña and Touchette, 2012). The emergence of such collective behaviors can be assessed and understood through the measurement of key synergistic properties such as degeneracy, i.e., the structurally different components that perform a similar (but not necessarily identical) function in a given context (Araújo and Davids, 2016). The degeneracy of team behavior as a social relationship property can be captured by Social Network Analysis (SNA) (Grund, 2012; Peña and Touchette, 2012). SNA has been applied to association football or soccer (Clemente et al., 2014b), in particular to analyze ball-passing networks in a team. These studies demonstrated that some metrics are useful to characterize styles of play and cooperation among teammates (Cotta et al., 2011, as well as the relation between individual actions and team tactical behavior (Passos et al., 2011). Centrality metrics have been used to identify the most influential tactical positions within a team. For example, by analyzing the in-degree and out-degree centrality of the Portugal national football team players, Mendes et al. (2015) found that during the FIFA World Cup 2014 the central midfielders were the key players in the attacking-building process. A similar study examining degree centrality and degree prestige of Switzerland national team players during the same competition showed that the key players receiving the ball were also the midfielders, suggesting this team has a style of play based on attacking building (Clemente et al., 2015b). Thus, network metrics such as density, heterogeneity and centralization are effective for characterizing the cooperation between players (Clemente et al., 2015a).

Analyses of network heterogeneity and centrality reveal that team offensive play has many variations and short patterns that increase collective unpredictability (Clemente et al., 2014b). Furthermore, high total links and high density can convey the team's greater ability to pass the ball between all players and to function as a whole, as well as to decentralize the network (Clemente et al., 2014a). For example, a study analyzing team ball-passing networks in 760 matches of the English Premier League (Grund, 2012) showed that high levels of network intensity were associated with increased team performance (goals scored), and centralized interaction patterns with decreased team performance. More recently, similar research analyzing ball-passing networks of teams competing at the FIFA World Cup 2014 (Clemente et al., 2015c) revealed significant differences in density, total links and clustering coefficient between teams reaching different stages of the competition. These findings further demonstrate an association between higher density, total links and clustering coefficient with performance variables such as goals scored, overall shots, and shots on goal (Clemente et al., 2015c). These findings were corroborated in youth football (under-15 and under-17) by Gonçalves et al. (2017), who observed that lower passing dependency for a given player (lower betweenness scores) and higher intra-team well-connected passing relations (higher passing density and closeness scores) may optimize team performance (number of shots). Also outside the scope of SNA important contributions were made to understand the effectiveness of collective behaviors and different tactical approaches. Thus, longer passing sequences, either in terms of number of passes (Hughes and Franks, 2005; Tenga et al., 2010a) or its duration (Lago-Ballesteros et al., 2012a) have been reported as more efficient to obtain goals (Hughes and Franks, 2005) or score-box possessions (Tenga et al., 2010a; Lago-Ballesteros et al., 2012a).

Despite these recent advances, research in the field has remained focused on the association between ball-passing network metrics and coarse-grained team performance variables (e.g., goals scored, shots, shots on goal, or competition stage reached) (Grund, 2012; Clemente et al., 2015c), which implies that team performance outputs and network properties metrics are measured simultaneously (Grund, 2012). However, since ball-passing network analysis offers an overall picture of events occurring during a certain period of time, typically a synthesis of several complete matches, the events leading to successful or unsuccessful team performance are included in the same analyses. Thus, it remains unknown whether specific network properties and successful (or unsuccessful) team behavior are associated. Furthermore, although previous research based on ball-passing networks suggests that high density (Clemente et al., 2015c) and low centralization (Grund, 2012) are associated with successful teams, the relation between clustering coefficients and team performance is more uncertain (Peña and Touchette, 2012; Gudmundsson and Horton, 2016). Thus, the aim of this study was to test whether team network density, centralization and clustering coefficient can be used to predict the outcome of offensive plays.

MATERIALS AND METHODS

Sample

This study deliberately focused on club-teams rather than on national teams because club-teams train and compete together for longer consecutive periods of time. Our sample comprises 12 matches played in Group C of the UEFA Champions League 2015/2016 Group Stage. The four teams analyzed are here identified as CAM, FCA, GSK, and SLB.

Procedures

Our analysis focused on collective offensive processes. Offensive play is a set of attacking actions performed by a team between recovering and losing ball possession. According to Garganta (1997) a team is in possession of the ball, and therefore in the attacking process, when any of its players respect, at least, one of the following conditions: (i) holds at least two consecutive contacts with ball, (ii) performs a positive pass (allowing the maintenance of ball possession), and (iii) performs a shot (finishing). We considered that a team is in possession of the ball once it completes a pass and maintains ball possession after the pass. Moreover, set-off passes were considered in the analysis.

The video footage used in the analysis was obtained from TV broadcasters. We started by categorizing all offensive plays as *successful* when the attacking team entered the *finishing zone*, which was previously reported as a proxy variable for scored goals when measuring successfulness in football (Tenga et al., 2010b). The concept of finishing zone was based on Gréhaigne et al.'s longitudinal division of the football field into four equal areas (Gréhaigne et al., 2001). These areas are designated according to the direction of the attack as follows: defensive zone, pre-defensive zone, pre-offensive zone and offensive zone. The offensive zone in elite soccer was defined as the finishing zone (Lago Ballesteros et al., 2012b).

Successful offensive plays (SOPs) include plays that finished with a shot at the goal and those where the team retained ball possession until entering the finishing zone. *Unsuccessful offensive plays* (UOPs) were all the plays where the team lost ball possession without meeting either of the SOP criteria. *Neutral plays* were offensive plays where a team did not lose ball possession but also did not meet the SOP criteria. This neutral category included all offensive plays that were initiated: (i) from an offensive corner kick; (ii) in an offensive throw-in; and (iii) from offensive free kicks with a first pass directly into the finishing zone. The neutral offensive plays were not included in the present analysis.

The offensive plays were identified and categorized with *Longomatch* software from every pass performed in the 12 matches. The players who passed and received the ball were registered for each offensive play. A number from one to 11 was assigned to each player according to his initial position within the team's tactical system. The same number was assigned to players performing the same tactical position. Taking into account their different stoppage times, each half of the match was divided into three fractions with the same duration. Next, two adjacency matrices of offensive plays (successful and unsuccessful) for each opposing team were created for the six periods of the match, in a total of 24 adjacency matrices per match. Each of these adjacency matrices was then imported to the software *NodeXL* to compute the networks and their metrics. All statistical procedures were performed using *SPSS Statistics 24*.

Predictor Variables

Density

Density is the interconnectedness of nodes (players) in a network (team), i.e., it is the ratio of existing ties (passes) between teammates relative to the possible number of such ties (Balkundi and Harrison, 2006). In ordered relations, as in the teammates interactions, the possible directed links in a digraph of n nodes are $n\ (n-1)$, as a unique pass between two players was operationally defined as a link. The graph's density Δ is defined as the ratio between the total registered links ($\mathcal{L}$) and the maximum number of possible connections. It is calculated as:

$$\Delta = \frac{\mathcal{L}}{n\,(n-1)}$$

Thus, density is a fraction with a minimum of 0 (no lines/arcs present) and a maximum of 1 (all lines/arcs are present) (Wasserman and Faust, 1994).

Clustering Coefficient

Clustering is a measure of the degree to which nodes in a network tend to cluster together (Peña and Touchette, 2012). The clustering coefficient, originally introduced by Watts and Strogatz (1998), quantifies how close a node and its neighbors in a graph are to becoming a complete subgraph.

In directed graphs, the local clustering coefficient of a vertex expresses the ratio of the links between the vertices that are connected to it. Thus, local clustering coefficient (C) of a given vertex i is the fraction of the number of connections a_{jk} between k_i vertices in its neighborhood, divided by the maximum number $k_i\ (k_i - 1)$ of possible links there between:

$$C_i = \frac{\left|\left\{a_{jk}, a_{jk} \in E\right\}\right|}{k_i\left(k_i - 1\right)}$$

We used a variant of the clustering coefficient—the average local clustering coefficient—to measure the clustering level throughout the network:

$$\bar{C} = \frac{1}{n}\sum\nolimits_{i=1}^{n} C_i$$

Centralization

The centrality of a group or network is the degree of inequality of the distribution of positions/"weights" of different elements within the network. A network is therefore more centralized when one of its elements is clearly more central than all other group members. Conversely, a network is decentralized when all its elements have the same value of centrality (Grund, 2012).

There are several measures of centrality and researchers do not always agree on how "group centrality" or "centralization" should be assessed. We used degree centrality for quantifying the relative influence of each player on the total number of passes within a network. Thus, centralization conveys how central the most central player is when compared to the other players in the network. This metric was originally described by Freeman (1978) and is calculated as the sum of the differences between the vertex with the highest degree centrality and all other vertexes; divided by a value depending only on the size of the network:

$$C_D = \frac{\sum_{i=1}^{n} \deg\left(v^*\right) - \deg\left(v\right)}{n^2 - 3n + 2}$$

where deg (v^*) is the largest value of centrality degree in the network, deg (v) is the value of each vertex centrality degree, and the denominator is the maximum possible sum of differences in $i = 1$ vertex centrality for a graph of n vertexes (Freeman, 1978).

In the context of a football match, zero centralization indicates that all players have the same level of interaction during the game. Conversely, a centralization value very close to one suggests that a player is the key-player of the team and that other players have a strong tendency to play with him (Clemente et al., 2015a).

Analysis

A hierarchical logistic regression model using the logit link function was performed to predict the successfulness of offensive plays from the number of passes performed and the network metrics (density, clustering coefficient and centralization). Two blocks were defined. In thefirst block, only the predictor *total* *passes* was introduced. In the second block, we introduced the network metrics. Thus, after controlling for the effect of total passes, we could estimate the specific effects of the network metrics. Preliminarily, the data was screened for collinearity problems and outliers and for linearity of the logit. Following the recommendations in (Belsley et al., 2005), we diagnosed collinearity when conditioning indexes were greater than 30 for a given dimension and the variance proportions were greater than 0.5 for more than one variable. The latter was true for the pairs of variables "clustering coefficient and centralization" and "total passes and density," however, both of these dimensions registered conditioning indexes below 30 (12.224 and 22.655, respectively). We tested all the metrics for linearity of the logit, running the logistic regression with all predictors and the interaction between each predictor and the log of itself in a single block. All four interactions had significance values greater than 0.05, indicating that the assumption of linearity of the logit has been met for total passes, density, clustering coefficient and centralization. Consequently, it was not necessary to transform or eliminate any predictor-variable. Next, we obtained z-scores and searched for outliers greater than 3.29 (Tabachnick and Fidell, 2013). A single outlier was identified (z-score = 4.378) and removed. Additionally, four SOP cases were removed because they registered "no passes." After these preliminary procedures, 283 of the initial 288 cases were kept for further analysis, corresponding to 144 cases of UOP and 139 of SOP.

In a logistic regression, Exp (β_i) represents the odds-ratio of success vs. failure (categories of the model's dependent variable) when variable X_i increases by one unit with respect to the odds-ratio of success vs. failure, when X_i stays constant. Density, clustering coefficient and centralization vary between zero and one, therefore, we converted these metrics to a scale of 0 to 10 to adjust to model sensitivity. Consequently, the odds ratios presented for these variables refer to a unit change of 0.1.

RESULTS

A two-block hierarchical logistic regression was used to predict the successfulness of offensive plays. In the first block, the total number of passes (hereafter referred to as 'total passes') was the only predictor-variable. This model performed significantly better than a constant-only model [$G^2_{(1,\,N=283)} = 7.484$, $p = 0.006$], it did not satisfy goodness-of-fit criteria (Hosmer and Lemeshow test: $\chi^2_{(8,\,N=283)} = 25.342, p = 0.001$), and it produced a Nagelkerke r^2 of 0.035. Network metrics were added in a second block (**Table 1**). This second model performed better than a constant-only model [$G^2_{(1,\,N=283)} = 15.484, p = 0.004$) and satisfied goodness-of-fit criteria (Hosmer and Lemeshow test: $\chi^2_{(8,\,N=283)} = 7.187$, $p = 0.517$), achieving a Nagelkerke r^2 of 0.071. The first-block model correctly classified 56.2% of the known cases, 66.7% of the UOPs and 45.3% of the SOPs. The second-block model correctly classified 69.5% of the UOPs and 47.5% of the SOPs, with an overall correct classification of 58.7% of the cases. Thus, adding the second block to the model increased the number of correct classifications by 2.5%.

Total number of passes and density were significant predictors among the four considered variables. The total number of passes

TABLE 1 | Binary Logistic Regression Model of offensive plays' successfulness.

	β (S.E.)	Wald	p	Exp (β)	Exp (β) 95% C.I	
					Lower	Upper
Total number of passes	0.079 (0.034)	5.475	0.019	1.082	1.013	1.156
Density scores	−1.320 (0.591)	4.994	0.025	0.267	0.084	0.850
Clustering coefficient scores	0.179 (0.193)	0.858	0.354	1.196	0.819	1.747
Centralization scores	0.189 (0.143)	1.759	0.185	1.208	0.914	1.597
Constant	−0.615 (0.469)	1.719	0.190	0.541		

Successful Offensive Play (SOP) is the reference category of successfulness predicted in the model.

was positively associated with the successfulness of offensive plays. A one-pass-increase augmented the probability of SOPs by 8.2% Exp (β) = 1.082; see **Table 1**). More significantly, a 10% decrease in density increased the chances for a successful offensive play by 73.3% (Exp (β) = 0.267; see **Table 1**). Furthermore, for density values ranging from 0 to 0.25 there is a similar relation between total passes and number of either SOPs or UOPs (see **Figure 1**), despite the higher frequency of UOPs (see **Figure 2**). However, for density values above 0.25, as density and total passes increases, we see a tendency for a decrease in both SOPs and UOPs, but a predominant occurrence of SOPs in relation to UOPs.

DISCUSSION

Network characteristics such as density, clustering coefficient and centralization have been reported as good descriptors of game style in soccer teams, as they can be associated with metrics of success such as goals scored, shots, shots on goal, and competition stage reached by teams. However, since network analysis describes events occurring during entire matches, performance outputs and network properties metrics cannot be measured simultaneously. In this study, we attempted to clarify the association between specific network properties and successful (or unsuccessful) team behavior.

Our model was able to classify 58.7% of the events correctly, however, it performed better at identifying UOPs (69.5%) than SOPs (47.5%). These results suggest that these network metrics (density, clustering coefficient and centralization) can more accurately describe the team behaviors associated with UOPs (i.e., losing ball possession) than the behaviors leading to SOPs (i.e., moving into the finishing zone or shooting on goal). Thus, despite the limited predictive power, the model seems to better pinpoint the collective behaviors that the teams should avoid rather than the ones that they should perform in order to ensure success.

The total number of passes and density were the most relevant variables in our model. Total passes was introduced in the first block of regression model to assess the specific influence of the network metrics on team performance. The improvement in

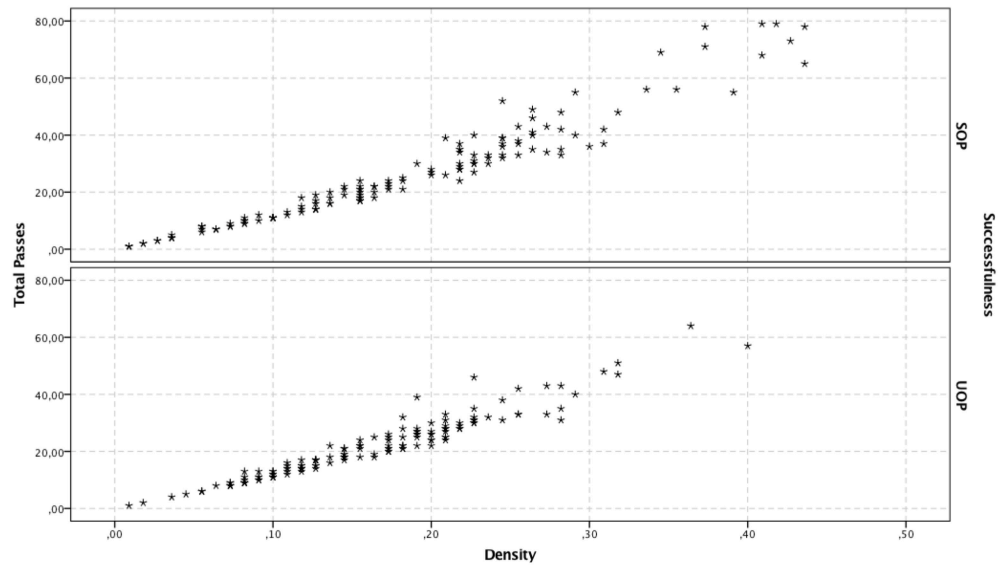

FIGURE 1 | Depiction case-by-case of the relationship between density and total passes, for SOP and UOP predicted outcomes, according to the second-block logistic regression model.

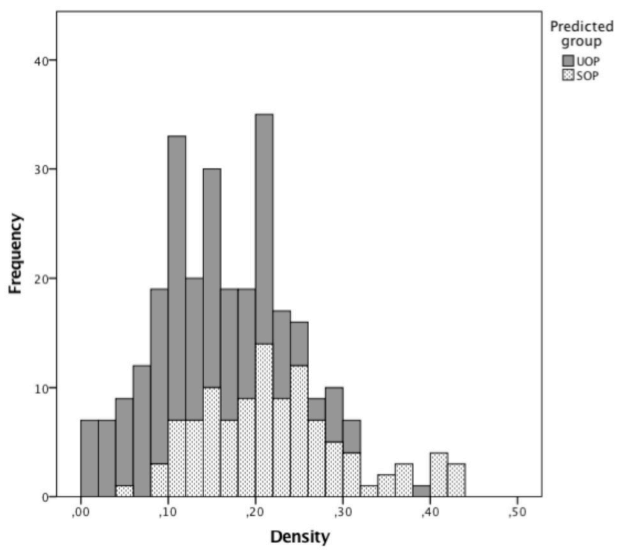

FIGURE 2 | Frequencies of density values, according to the category of offensive play's successfulness.

the model obtained by adding the second block confirmed the metrics' specific influence. We observed a positive association between total passes and team performance. Each new pass in a set of offensive plays occurring within a 15 min-period resulted in the teams being 8.2% more likely to move into the finishing zone or to shoot on goal. These findings corroborated the studies that showed that long passing sequences are more efficient than short passing sequences (Hughes and Franks, 2005; Tenga et al., 2010a; Lago-Ballesteros et al., 2012a). The density of a ball-passing network increases whenever two players who were not yet connected pass the ball between them; in this way, high density is probably associated to high occurrence of these differentiated links. This greater variability of pass patterns, which is expressed in qualitatively distinct connections over a given period, may occur for different reasons. For example, greater collective dynamics and high player mobility can result in passes between players who regularly play in distant areas.

It has been shown that strong cooperation between teammates makes teams stronger and more successful (Balkundi and Harrison, 2006). Thus, how can we explain our results showing that density has a negative effect (albeit small) on the successfulness of offensive plays? As can be seen in **Figure 2**, for density values ranging from 0 to 0.25 our model predicts more UOP than SOP outcomes. When we consider only events classified as SOP, there is a high number of offensive plays with density values ranging from 0.1 to 0.25, followed by a decrease. This drop in the number of offensive plays for higher density values could explain the negative association between density and SOPs. Indeed, despite being associated with fewer SOPs overall, higher densities are more likely to lead to SOPs (see **Figure 1**). Thus, our results suggest that density values lower than 0.25 are associated with a higher number of offensive plays, albeit mostly unsuccessful ones. Conversely, for density values above 0.25 there may be fewer offensive plays overall but most are successful. It is unlikely though that this negative association between density and SOPs is simply due to the higher number of errors and losses that result from the players' greater efforts to maintain connections in high-density scenarios (Burt, 1997). Instead, it seems more plausible that the reduction in SOP outcomes observed for density values above 0.25 explains that negative association. Indeed, these offensive plays with high-density values are characterized by a higher number of passes (see **Figure 1**), which could explain why there are fewer (but more successful) offensive plays in the same period of time. For example, these high-density values may result from longer ball-possession times, fewer ball possession losses, or specific losses in advanced zones of the field (finishing zone). These results are in line with findings of Hughes and Franks (2005), who reported that the association between short offensive sequences and high number of goals was directly related to the greater number of these sequences but not to their efficiency. When the results were normalized by the number of offensive plays, it was observed that the longer offensive plays were more efficient. This hypothesis is consistent with our observation that qualitatively differentiated links are associated with high densities, which likely reflects a greater unpredictability of passing patterns. Furthermore, it was previously proposed that greater variability of action and less exposure to the opponent could result from decentralized passing patterns (Gréhaigne et al., 1997). Such characteristics of offensive plays associated with high-density values contribute to an offensive process that creates goal-scoring opportunities and are more effective for maintaining ball possession in advanced areas. Interestingly, offensive plays with similar characteristics have been observed in successful teams at the FIFA World Cup 2014 (Clemente et al., 2015c) and in under-15 and under-17 football teams (Gonçalves et al., 2017).

We found that the clustering coefficient is not a significant predictor of the successfulness of offensive plays, thus corroborating previous research (Peña and Touchette, 2012; Gudmundsson and Horton, 2016). High clustering coefficient values express the subgroup formation within the team itself; when these subgroups are created based on passes between teammates, as in the present study, the players performing in close areas tend to be linked together, thereby explaining the high clustering coefficients. This could reflect an offensive style choice based on short combinations between players, as previously observed for the Spain, Germany and Netherlands national teams at the FIFA World Cup 2010 (Cotta et al., 2011; Peña and Touchette, 2012). Thus, the modest contribution of the clustering coefficient to the predictive value of our model suggests that different offensive styles may lead to successful team performance, depending, for example, on the players' individual qualities or on different strategic options. Further investigation is needed to clarify this issue. Our results also demonstrated that centralization is not consistently associated with successfulness of offensive plays, which is in agreement with findings by Fewell et al. (2012) showing that there is no strong relationship between centralization and team performance. Results didn't corroborate previous reports showing that higher centralization is associated with worse team performance (Grund, 2012; Gonçalves et al., 2017). This discrepancy could, however, be explained by the different methodologies in these studies, as discriminating successful and unsuccessful performances probably influenced the relationship between centralization and successful team performance in our study.

In summary, our results suggest that network density contributes to the prediction of a team's ability to enter in the finishing zone or to shoot at the goal in elite football matches. Furthermore, this study gives new insights into the association between network density and team performance (Balkundi and Harrison, 2006). First, we showed that low network density may be associated with a higher overall number of offensive plays but which are mostly unsuccessful. Second, high density was associated with fewer and/or longer offensive plays, which reduces the possibilities of a team moving into the finishing zone (hence decreasing total SOPs), thus resulting in a negative association between density and SOPs. Finally, we considered that high density may also be associated with fewer ball-possession losses before the teams reach the finishing zone (hence increasing probability of SOPs), thereby supporting the density-performance hypothesis.

Some practical implications can be drawn from the present findings. Teams that express high densities in their offensive process may lose possession of the ball in the advanced zones, This facilitates, for example, more space on the back of the defensive line and the need to control this space by efficient pressing in zones of loss. Furthermore, the establishment of varied links by a team is eventually dependent on the creation of numerous lines of pass to the player with the ball. In light with ecological dynamics (Araujo et al., 2006), it might be enhanced in the training sessions by the manipulation of task constraints, such as: (i) using different relationships between depth/width of field, to make a team enter the finishing zone by different space channels and, consequently, using differentiated links; (ii) performing possession games with numerous mini-goals dispersed in the field, so that the player with the ball searches for 360° pass lines (all around him/her); (iii) performing games with variation of the relationship between the number of players and the size of the field, to induce variability in the distance of the pass lines and the type of pass required. On the other hand, teams that express less density in their offensive plays must be prepared for more losses of ball possession, most probably in areas closer to their goal. In addition, to be offensively successful with more constant links among teammates (less new links), maybe some useful task constraints might be: (i) establishment of a time limit for the performance of offensive plays, in order to enhance the entries in the finishing zones with few connections; (ii) performing small-sided games with few players (1×1, 2×2, 3×3) to promote brief attacking actions with stable connections; (iii) improving relationships between specific players, according to preferential links, by placing such players in the same team in small-sided games or in the training of specific collective actions among them.

We tested a model that analyzes the specific associations between the characteristics of a team's ball-passing network and the outcome of its offensive plays (entering the finishing zone and shot on goal vs. losing ball possession). Previous studies had not differentiated these different outcomes, which may explain our results revealing a negative relation between density and team performance. Additionally the limited predictive power of the model may be associated with some limitations of the study such as the reduced number of teams and games analyzed, which may influence the findings due to the specific style of play of the four teams and eventually by the intra- and inter-team synergies created in the matches among them. Finally, we demonstrated that neither clustering coefficient nor centralization are significant predictors of team performance successfulness, possibly indicating that diverse offensive styles can be equally effective for a team to succeed.

AUTHOR CONTRIBUTIONS

TP had a major contribution to study conception and design, acquisition of data and analysis and interpretation of data. AP had a major contribution to analysis and interpretation of data. DA had a major contribution to study conception and design and analysis and interpretation of data.

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More Stable Ties or Better Structure? An Examination of the Impact of Co-author Network on Team Knowledge Creation

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This study aims to explore the influence of co-author network on team knowledge creation. Integrating the two traditional perspectives of network relationship and network structure, we examine the direct and interactive effects of tie stability and structural holes on team knowledge creation. Tracking scientific articles published by 111 scholars in the research field of human resource management from the top 8 American universities, we analyze scholars' scientific co-author networks. The result indicates that tie stability changes the teams' information processing modes and, when graphed, results in an inverted U-shape relationship between tie stability and team knowledge creation. Moreover, structural holes in co-author network are proved to be harmful to team knowledge sharing and diffusion, thereby impeding team knowledge creation. Also, tie stability and structural hole interactively influence team knowledge creation. When the number of structural hole is low in the co-author network, the graphical representation of the relationship between tie stability and team knowledge creation tends to be a more distinct U-shape.

Keywords: tie stability, structural hole, knowledge creation, collaboration, network

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INTRODUCTION

As knowledge is important to the development of society and organizations, there is a burgeoning interest on how to create more knowledge in scientific research (Lambiotte and Panzarasa, 2009). Traditionally, scholars have focused on the role of individual personality or talents on knowledge creation (e.g., Bowler and Morus, 2010). However, recent knowledge management researchers are shifting their attentions from the individual factors to team factors (Wuchty et al., 2007). Given knowledge creation is becoming more and more complex, researchers build teams in order to meet their knowledge creation goals. This shift poses a challenge for researchers: how can teams manage the process of knowledge creation successfully?

The majority of research adopts the paradigm of "input-process-output" model to explore the antecedents and process of team knowledge creation. Following this model, researchers suggest that team diversity such as educational background, gender, age diversity (Smith et al., 2005), leadership behavior (Nonaka et al., 2006) and organizational policies (Argote et al., 2003) are critical antecedents of team knowledge creation. They also identify team learning (Stacey, 2001), team members' motivations (Sosa, 2011) and feedback (Akbar, 2003) as key processes that stimulate team knowledge creation. However, prior research mainly focuses on the effects of teams' cognition or behaviors among team members on team knowledge creation. This approach fails to capture the influence of team members' interactions on team knowledge creation. Team knowledge creation refers to a continuous, self-transcending process during which team members obtain, absorb and integrate valuable external knowledge through their interaction with others (Nonaka et al., 2000). This process emphasizes team members' interactions (Schumpeter, 1934; Polanyi and Sen, 1967). Thus, some researchers introduce social networks theory to investigate team knowledge creation.

Social network theory offers theoretical lens to analyze the influence of embedded relationship on individual or team's behavior. Generally, previous studies explore network effects manly from two different perspectives (Moran, 2005). The first perspective focuses on the direct tie effects such as tie strength (i.e., the mean frequency interactions among actors) on organizational outcomes (e.g., Labianca and Brass, 2006). The second perspective, from a macro level, posits that the network structure such as network density (i.e., ratio of extant edges to potential edges) plays the most important role on shaping individual or team's behavior (e.g., Galaskiewicz and Burt, 1991; Burkhardt, 1994). These two streams have pushed social network study forward tremendously. However, due to the lack of comparative and comprehensive study on the two perspectives, we know little about the exact role that network structure and directive tie states play in the team knowledge creation process. Importantly, we do not know whether these two aspects have interactive effects on team knowledge creation. Hence, this study attempts to address this knowledge gap by choosing specific variables from these two different perspectives and comparing the direct effects of these variables while examining the interactive influence of the two network perspectives on team knowledge creation.

Existing studies of direct ties mainly focus on the effect of interactive frequency among actors, i.e., tie strength, on knowledge creation. For example, McFadyen et al. (2009) find that average tie strength is one of the critical factors that influencing knowledge creation. However, the majority of these studies have overlooked the time aspect of the ties. This is problematic because the same interaction between two actors may occur in 1 day, it may also happen in 1 month or even 1 year. If researchers only focus on frequency, there is no way for us to know if the ties among actors are stable. Further, we will not clear about whether tie stability (i.e., keeping a certain relationship for a long time) will benefits team knowledge creation. Therefore, we will first examine the relationship between tie stability and team knowledge creation.

Considering the studies focus on network structures, researchers mainly emphasize two critical variables, i.e., network density and centrality. For example, network density, defined as the proportion of potential ties in a network that are actually present (Ahuja et al., 2012), has been identified as impeding factor of knowledge creation (McFadyen et al., 2009), and centrality, defined as the extent to which a network revolves around a single node, has been proven to have positive effects on knowledge creation (Matusik and Heeley, 2005). However, structural hole, referring to the acts that serve as mediators between two or more closely connected groups, has been considered as an very important attribute of network structure (Burt, 1992), few studies have examined the relationship between structural hole and team knowledge creation. In addition, both attributes of tie and structures may interactively influence team knowledge creation. To our knowledge, few studies have examined the interactive effect of tie stability and structural hole on knowledge creation. Therefore, the second aim of this study is to examine the direct effect of structural hole as well as the interactive effect of tie stability and structural hole on team knowledge creation.

The present study contributes to the knowledge creation literature in two aspects. Firstly, despite some links existing between ego network and individual knowledge creation (e.g., Smith et al., 2005), we know surprisingly little about how new knowledge is created in teams (McFadyen and Cannella, 2004; McFadyen et al., 2009). This study sheds light on this aspect by identifying the influences of co-author network on team knowledge creation. Secondly, we intend to integrate the two different perspectives, i.e., network structure (structural holes) and network tie attribution (tie stability), to examine the direct and interactive effects of the two on team knowledge creation. Prior studies either examine the effect of tie attribution such as tie strength on knowledge creation (e.g., Levin and Cross, 2004), or identify the network structure, such as density and centrality on knowledge creation (e.g., Gilsing et al., 2008). There is no theoretical and empirical evidence of how these two aspects of network interact simultaneously. This study adds value on the influence of co-author network on team knowledge creation.

THEORETICAL BACKGROUND

Knowledge creation is a continuous, self-transcending process during which individuals obtain, absorb and integrate valuable external knowledge through their interaction with others (Nonaka et al., 2000). It is affected by individuals' current knowledge system and external knowledge processing environment. This process, to some extent, is an information processing process. Although individual and collective processes of knowledge creation are similar, the only difference between them is that the individual process emphasizes the integration of knowledge in one's mind; whereas the collective process emphasizes the interaction among team members Lavie and Drori (2012). Information is the input to teams and new knowledge output via the interactions among team members. Collective information processing theory involves a prerequisite assumption that task-relevant information is acquired and shared among team members (De Dreu et al., 2008). In other words, team members comprehend and process the new information they have acquired from each other or the external world and form a new collective understanding of the real. Hence, if all members are regarded as an information processing agent, team knowledge creation can be further recognized as a collective information process. We define team knowledge creation as a process of collaborative group performance, during which team members collectively amplify the knowledge created by some individuals and crystallize it as part of the knowledge system of the team (Nonaka et al., 1996; Mitchell et al., 2009).

Team members' interactions allow information transfer, process and development into common cognitive at the team level. Klein and Kozlowski (2000) elaborate two ideal modes of the emerging of collective knowledge in team information processing. The first one is composition. Composition emphasizing the assumptions of isomorphism and treats, regards team cognition as a convergence of similar cognitive properties at the individual level. It describes the generating process of new knowledge from the lower-level to the higher-level and the consistency of individual knowledge and systematic cognition. The second mode is compilation. Based on assumptions of discontinuity, compilation describes the combination and restructuring of differentiated knowledge during information processing by emphasizing essential functions of differentiated knowledge. Therefore, we suggest that these two information processing processes supplement each other in team knowledge creation. In particular, composition process emphasizes the integration of homogeneous knowledge, thereby forming the optimal solution, compilation process, which underlines the role of heterogeneous knowledge, ensures that knowledge could be extended.

HYPOTHESES

Effect of Tie Stability on Team Knowledge Creation

We define tie stability as the proportions of team members who maintain a long time cooperative relationship with others (Huggins, 2010). The higher the tie stability is, the larger the proportions of members who have maintained a long time cooperative relationship with other team members. Tie stability emphasizes the time aspect of the tie rather than the frequency aspect. Some scholars find that stable relationships may enhance the transfer of tacit knowledge and thus be beneficial for knowledge creation (Ebadi and Utterback, 1984; Moran, 2005), while others argue that changes in cooperative relations motivate a team to transform its conventional thinking, thereby helping maintain knowledge heterogeneity and promoting team members to generate novel ideas (Choi and Thompson, 2005). Also, according to similar theory, if team members interact with each other too long or too frequently, the information or knowledge they possess will step toward a similar trend (Lewis et al., 2007).

We believe tie stability is like a double-edged sword in that it will change teams' information processing modes. According to the collective information processing theory, composition process emphasizes the identical facet of knowledge, believing homogeneity is the basis for the combination of heterogeneous knowledge. By contrast, compilation process emphasizes the heterogeneity aspect of knowledge, regarding the variety of knowledge as the impetus for knowledge development and deepening (Klein and Kozlowski, 2000). We assume that team knowledge creation could not be realized only with one of these two processes. Alternatively, only when the two processes reach a balanced proportion can collective knowledge creation be effectively promoted. The reason lies in that the homogeneous aspects of knowledge provide convenience for knowledge combination (Pinjani and Palvia, 2013), whereas, the heterogeneous aspects of knowledge provide possibility for knowledge expansion (Swan et al., 1999).

As mentioned previously, tie stability represents the proportions of members who have maintained an enduring cooperative relationship with other team members. If a team's tie stability is high, indicating that the team members' interaction with each other is frequent, this condition is beneficial for knowledge combination within the team. However, too much interaction among team members may lead to a similar tendency of their knowledge and thinking (Huggins, 2010), which may impede their knowledge expansion and further harm team knowledge creation (Lewis et al., 2007). In other words, tie stability may determine the information process mode in the team, which in turn influences the team knowledge creation. When tie stability is low, a context for developing heterogeneous knowledge, will promote the information processing mode of compilation. By contrast, when tie stability is high, a context for developing homogeneous knowledge (Huggins, 2010), will trigger the information processing mode of composition. Therefore, if tie stability is moderate, compilation and composition may reach a balance, this context will greatly benefit to team knowledge creation. We propose the following hypothesis:

Hypothesis 1: There is a U-shaped relationship between tie stability and team knowledge creation. Specifically, moderate tie stability benefits team knowledge creation, whereas lower and higher tie stability result in poor performance in team knowledge creation.

Structural Holes and Team Knowledge Creation

The concept of the structural hole was established by Burt (1992). It describes social networks where two or more individuals build indirect connections by connecting to a third party but no direct relationships exists between them. Prior research suggests that structural hole brings many advantages and conveniences to individuals who occupy the position of structural holes. For instance, Burt (2004) points out that individuals occupying structural holes can embrace more opportunities of gaining information or resource from others as they bridge two or more individuals. Frankort (2008) notes that structural hole elevates individuals' performance and creativity as it reduces information redundancy and provides people more opportunities to access heterogeneous information. Nevertheless, with regards to team knowledge creation, structural holes might do more harm than good.

As mentioned previously, team knowledge creation can be regarded as a collective information processing process. This process emphasizes information and knowledge sharing. Structural hole focuses on the relationship of team members reach out to each other by the third party rather than by direct connection. This indirect connection undoubtedly results in difficulty in information flows between them. If a team contains many structural holes, the proportion of team members' non-direct communication will increase. As a few members within the structural holes largely control the internal information of a team, knowledge and information sharing will become difficult. Furthermore, information transferred through the third party may result in some distortion, thereby hindering internal team information flows. Obstfeld (2002) suggested that the increase in structural holes inevitably affects team creativity as the structural holes indulge team members' opportunistic behaviors, which obstructions for the transmission of information. Therefore, a team with more structural holes tends to have more difficulties in information sharing, giving rise to disadvantages for team knowledge creation. Following this analysis, we propose the second hypothesis:

Hypothesis 2: Structural hole in co-author network is negatively related to performance quality of team knowledge creation.

Interactive Effect of Tie Stability and Structural Holes

As mentioned above, the degree of co-author network tie stability determines the proportion between homogeneous and heterogeneous elements of information transfer among team members. The number of structural holes influences the fluency and efficiency of knowledge exchange. According to information processing theory, information processing, basing on information sharing and exchanging among team members (De Dreu et al., 2008), is a critical factor for team knowledge creation. Specifically, when a team enjoys high efficiency in information transfer and sharing, the speed in integrating its homogeneous and heterogeneous knowledge or information can be accelerated, which leads to improvement of the efficiency in team knowledge creation. By contrast, when the sharing of team information is hindered, the homogeneous and heterogeneous information is not exchanged effectively, and team knowledge creation is impeded.

As mentioned previously, structural hole influences the efficiency of team knowledge creation by disturbing information sharing and exchange process within the team. If a team's co-author network includes too many structural holes, information transfer will be difficult among team members (Ahuja, 2000), and will impede team knowledge creation. Although tie stability may increase the possibility of information exchange among team members, this beneficial effect may be offset by the negative impact of high structural hole. Also, as a team's tie stability increases, team members increasingly interact within the team, leading team members' information and thinking to a similar trend and thus hindering team knowledge creation (Huggins, 2010). However, studies indicate that structural hole can increase heterogeneous information, because it increases possibility of accessing information from different parties (Burt, 2004). Hence the negative effect caused by high stability may also be offset by high structural holes. Therefore, in teams with high structural hole, the U-shaped relationship between tie stability and team knowledge creation would be weakened and trend to be more linear.

The increase of co-author network's tie stability in an appropriate extent will benefit information transfer and exchange within the team, thereby promoting team knowledge creation. However, if a team's co-author network possesses the low structural hole, information transfer efficiency will benefit (Balkundi et al., 2007). Hence, the positive relationship between tie stability and team knowledge creation in the appropriate extent will be strengthened in teams with low structural hole. In addition, if a team's tie stability increases to an excessive extent, team members' increased interaction will lead to homogeny of team members' information, and thus hinder team knowledge creation (Huggins, 2010). A low structural hole context which also benefits to information transfer within the team may also strengthen the negative effect caused by high tie stability. Based on the arguments above, we propose the third hypothesis.

Hypothesis 3: The inverted U-shape relationship between tie stability and team knowledge creation is moderated by the number of structural holes. Specifically, when there are less structural holes, the inverted U-shape relationship between the two would be amplified; when there are more structural holes, this relationship would be significantly weakened, and trending to be a more linear relationship.

METHOD

Sample and Procedure

First, we selected eight top academic institutions in the United States based on the widely recognized rankings by experts in human resources management. Then, we accessed school websites of these eight academic institutions to obtain the names and resumes of scholars in human resources management. Through this process, we gathered 191 qualified scholars. By collecting their published papers from 2005 to 2009 on the Institute for Scientific Information (ISI) database and tracking their coauthors, we captured every scholar's research co-author network. As the data on impact factors of journals were relatively complete from 2005 to 2009, we designated these 5 years as our research period. Since scholars may use different surnames and abbreviated forms while publishing during their academic career, to achieve a complete data set, we searched all different probable surnames and abbreviated forms within the given period in ISI database. Through the process of screening and data, we identified 111 scholars in these eight academic institutions. Starting from these scholars we identified and tracked co-authors to develop our co-author networks for research. The sample includes 862 scholars and 591 published academic papers. In addition to this, we also recorded information such as authors' names, gender, paper titles, journal titles, publishing year, impact factors for journals, citation frequency, years after obtaining Ph.Ds.

We also would like to note that the data is objective and valid from ISI website. Also, the research has been performed in accordance with the recommendations of the Science and Technology Research Office of Huazhong University of Science and Technology. There were no unethical behaviors in the research process, and we were exempt from further ethics board approval since our study did not involve human clinical trials or animal experiments.

Measures

Tie Stability

Tie stability refers to the degree of stable co-author relations in networks. Prior researchers have proposed a similar variable concept. For example, McFadyen et al. (2009) has applied "number of long-term coauthors" to measure collaboration relationships that lasted for 6 years or more. It is a way to measure the number of members who maintain stable co-author relations with others. However, we deem that time of collaboration is also an important embodiment of tie stability. Given that completing two papers in a top journal must be a long time commitment (usually more than about 4 years), we assumed that if two scholars have published two or more papers together, they maintain a stable relationship. We calculated the proportion of stable relationships to represent the tie stability of team (i.e., the number of team members who have published two papers with the same co-author divided by the number of team members). Based on this calculation, the minimum value of the ratio is "0," denoting that no stable ties exist among coauthors; while the maximum is "1," meaning that all of the coauthors in network are maintaining stable relationships.

Structural Holes

We employed research methods proposed by Burt (1992) to calculate the number of structural holes in co-author networks. Using matrix data of the co-author network, we adopted Ucinet 6 social network analysis software to calculate structural holes index of each team network.

Team Knowledge Creation

We adapted quality and quantity as two criteria for the evaluation of team knowledge creation. We used the journal's impact factors of each publication to assess quality. For quantity, we used the total number of papers published. Then we calculate the impact factors for all of the articles published to evaluate team knowledge creation. The journal impact factors considered were the values reported for the publication year of each study. McFadyen et al. (2009) also used impact factor of journals to access knowledge creation.

Control Variables

To control differences in scholars' genders (male = "0," female = "1") and knowledge, we included gender, years after gaining Ph.Ds., the ratios of first authored and last authored publications as control variables. Besides, as tie strength (the interactive frequency between two actors; Granovetter, 1983) is a variable which is similar to tie stability, we control the tie strength of network members to differentiate the influence of tie strength and tie stability on team knowledge creation.

RESULTS

Descriptive Statistics

Table 1 presents the mean, standard deviation and correlation coefficients for each variable. It shows that among the scholars, the average number of years after gaining a Ph.D. was 17.53 years, and 71% of those scholars were male. Besides, tie strength was positively related to tie stability ($r = 0.45$, $p < 0.01$), and tie stability had positive correlation with team knowledge creation ($r = 0.27$, $p < 0.01$), structural holes displayed a strong negative correlation with team knowledge creation ($r = 0.27 = -0.60$, $p < 0.01$). These result preliminarily supported our hypothesis 2.

Regression Analysis

Table 1 shows that the mean of "years after gaining Ph.D." is 17.53, and the mean of "team knowledge creation" was 12.61, which were far larger than the average mean of other control variables and independent variables. In order to reduce the bias of estimation, we first used logarithm to address "years after gaining Ph.D." to diminish difference in mean, and then ran negative binomial regressions to analyze the data. Before the analysis, we standardized all independent variables in case of multicollinearity. In the following step, we entered all control variables and added tie stability and its quadratic term into the model to examine hypothesis 1. Then we added structural hole to examine hypothesis 2. To test hypotheses, we further added interaction terms of structural holes and tie stability into the model. Detailed results of the negative binomial regression are reported in **Table 2**.

Hypothesis 1 predicts an inverted U-shape relationship between tie stability and team knowledge creation. Statistically, if the regression coefficient of tie stability squared is negative, significant and the model goodness of fit is better than the controlled model, this hypothesis will be supported. As shown in **Table 2**, the coefficient of tie stability quadratic term was negative and significant ($\beta = -0.43$, $P < 0.01$, *Model 3*). Meanwhile, relative to Models 1 and 2, adding quadratic term of tie stability accounts for 0.07 and 0.06 increase of ΔPseudo R squared statistic, respectively (ΔPseudo $R^2 = 0.06$; LR chi$^2 = 77.83$, $P < 0.01$; *model 3*) indicating a better goodness of fit. Thus, Hypothesis 1 was supported. Hypothesis 2 predicts that the number of structural holes is negatively related to team knowledge creation. Statistically, if the regression coefficient of structural hole is negative and significant and the model goodness of fit is better than the controlled model, this hypothesis will be supported. As shown in **Table 2**, the coefficient of structural holes was negative and significant ($\beta = -0.81$, $P < 0.01$, *Model 4*). Compared to control model, the goodness of fit of the model was increased significantly (Pseudo $R^2 = 0.18$;

TABLE 1 | Mean, standard deviation, and correlations.

	Mean	*SD*	1	2	3	4	5	6	7
(1) Gender	0.71	0.46							
(2) Years after obtaining Ph.D.	17.53	10.8	0.01						
(3) Proportion of first authored papers	0.42	0.34	−0.01	0.01					
(4) Proportion of last authored papers	0.27	0.30	−0.01	0.07	−0.51**				
(5) Tie strength	0.61	0.28	0.12*	0.03	0.27**	−0.08			
(6) Tie stability	0.20	0.26	0.13	0.03	−0.03	0.00	0.45**		
(7) Structural holes	0.55	0.30	−0.02	0.16	0.04	0.15	0.10	−0.01	
(8) Team knowledge creation	12.61	13.74	0.16	−0.15	−0.05	−0.00	0.27**	0.27**	−0.60**

*N = 111, *p < 0.05 (two-tailed test), **p < 0.01 (two-tailed test).*

TABLE 2 | Results of regression analysis.

Variables		Team knowledge creation				
		M1	M2	M3	M4	M5
Control variables	Constant	3.30**	3.11**	3.01**	2.26**	2.12**
	Gender	0.23	0.21	0.17	0.16	0.16
	Years after gaining Ph.D.	−0.27*	−0.26*	−0.17*	−0.11	−0.10
	Proportion of first authored papers	−0.63	−0.34	−0.11	−0.02	0.19
	Proportion of last authored papers	−0.30	−0.07	0.26	0.33	0.40
	Tie strength	0.48**	0.31*	0.26**	0.45**	0.34**
Predictive variables	Tie stability		0.31*	0.81**		0.25**
	Tie stability^2 (H1)			−0.43**		−0.12
	Structural holes (H2)				−0.81**	−0.83**
	Tie stability*structural holes					−0.25**
	Tie stability^2*structural holes (H3)					0.13*
	Pseudo R^2	0.03	0.04	0.10	0.18	0.20
	ΔPseudo R^2		0.01	0.06		0.02
	LR chi^2	27.57**	32.77**	77.83**	138.76**	155.99**

*N = 111, *p < 0.05 (two-tailed test), **p < 0.01 (two-tailed test).*

LR chi^2 = 138.76, $P < 0.01$, *Model 4*), thus supporting hypothesis 2.

Hypothesis 3 predicts that the interaction between tie stability and structural holes has impact on team knowledge creation. Statistically, if the regression coefficient of tie stability squared × structural hole is significant and the model goodness of fit is better than the controlled model. In addition, the interactive graph pattern trends consist with the proposition, then, this hypothesis will be supported. As shown in **Table 2**, Model 5 shows that the coefficient of the interaction term of tie stability squared × structural was significant ($\beta = 0.13$, $p < 0.05$; *Model 5*). When the interaction term were entered, Pseudo R^2 indexes increased 50% relative to Model 3 and 11.1% (Pseudo $R^2 = 0.20$; LR chi^2 = 155.99, $P < 0.01$, *Model 5*) relative to Model 4. In order the present the whole trends of the interactive pattern, we used two standard deviations above and below the mean of tie stability and one deviation above and below structural hole as criteria to plot the interaction diagram (Cohen et al., 2013). As shown in **Figure 1**, when the structural hole was low, the inverted U-shape relationship between tie stability and team knowledge creation became more distinctive; In contrast, when structural hole was high, the relationship between the two became flatter, and displayed a more linear shape. These results provide support for Hypothesis 3.

DISCUSSION

Theoretical Implications

As a crucial cognitive resource in organizational management, knowledge creation occupies a pivotal position in the knowledge management field. Scholars appeal further exploration to this issue so as to reveal its internal mechanism and important factors. To compensate for the limitations of prior research in psychological and cognitive perspectives, we applied the social network perspective and combined ideas of collective information processing theory to examine the interactive effect of research co-author networks and structure on team knowledge performance. Our study has extended previous research in several aspects:

First, the present research focuses on the impact of tie stability on team knowledge creation in co-author networks. Extensive research at the micro level concentrates on the influence of tie strength or relation object on creative thinking (Baer, 2010). Tie

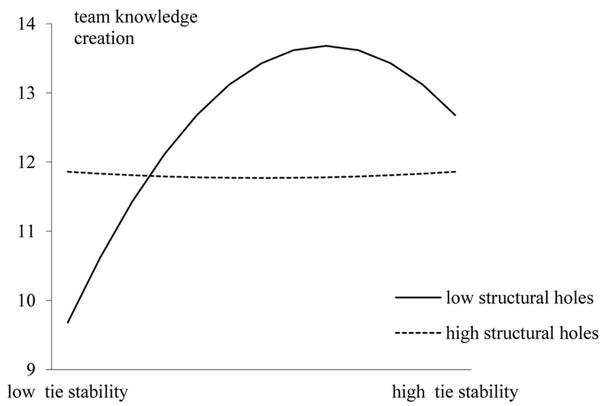

FIGURE 1 | Interaction Effect of Structural Holes and Tie Stability (±2*SD*).

strength reflects the tightness of direct interactions among team members, emphasizing the communication frequency among cohorts (Granovetter, 1983). Our study illustrates tie stability among group members and the general flow of coauthor-network and its percentage from tie stability perspective. It contributes to previous research by applying a new scope to analyze the effect of tie on team knowledge creation and extends our understanding of this issue.

Second, previous studies have generally examined the effects of network centrality, network density and number of sub-groups on team performance (e.g., Brass et al., 2004). In contrast, this study selects indexes of structural holes as research variable, which enriches our understanding of network structural effects on team knowledge creation. Though sparse studies have explored structural holes, they tend to focused on individual level and drew positive conclusions as researchers believe individuals occupying structural holes have the advantages of accessing to more and different information and resources (Soda et al., 2004). Approaching from a team level scope, our study provides evidence that the number of structural holes has negative effect on team knowledge creation, revealing the dark side of structural holes.

Finally, by combining the perspectives of co-author networks tie state and structure pattern, we seek to explore the interactive effect of the two on team knowledge creation. Although few previous studies have examined the two perspectives, respectively (e.g., Smith et al., 2005), studies approach from the comprehensive view are rare. We find evidence that tie stability and structural hole would interactively influence team knowledge creation by intervening the information processing process within the team. The results indicate that the effect of tie state, such as stability, on team knowledge creation might be weakened or strengthened by network structural pattern, such as structure hole. Prior studies either explore the effect on team knowledge creation from the perspective of tie state or from the perspective of network structural. These studies have identified that both tie state and structure pattern have significant impact on team knowledge creation. However, prior studies overlook that this two perspectives may have interrelationship. The present study examining the interactive effects of the two different perspectives provides new understanding of the relationship between network and team knowledge creation.

Managerial Implication

Knowledge is created during individuals' interaction with others rather than generated in isolation (Phelps et al., 2012). Only through comparing his or her own idea with others' can individual improve their understanding of specific issues. From this perspective, knowledge creation is team work. Therefore, the relational schema of team members' co-author networks must affect team knowledge creation. The results of this study also suggest some managerial implications for organization practice. Firstly, team members need to maintain both stable and flowing relations with others properly. Stable tie is a foundation for team members to form convergent and integrated knowledge; while tie state provides team with heterogeneous knowledge resources and information. Organizations need to balance the homogeneous and heterogeneous knowledge formed as a result of tie stability to help team members synthesize information.

Further, the network structure among team members determines the efficiency of knowledge transfer and sharing which are the foundations of knowledge integration, influencing team knowledge creation Reagans and McEvily (2003). For business organizations, advantages in policies need to be given a full play to shape the collaborative networks among team members and thus to develop the structural benefits of cooperative networks. For example, research teams can properly adjust and shape network coauthor relation to reduce the occurrence of structural holes and increase the density of co-author networks tie to increase the speed and efficiency of knowledge and information sharing.

Finally, by combining the perspectives of co-author networks tie state and structure pattern, we seek to explore the interactive effect of the two on team knowledge creation. A few previous studied have examined the two perspectives, respectively (e.g., Smith et al., 2005), while studies approached from the comprehensive view are rare (Phelps et al., 2012). We find evidence that tie and structure have interactive influencing on team knowledge creation. Both Tie stability and structural hole can influence the efficiency of team knowledge and information sharing and transfer, and hence have impact on team knowledge creation. In other words, co-author network direct tie and structure pattern have interactively influence on team knowledge creation.

LIMITATIONS AND FUTURE RESEARCH DIRECTIONS

Although the present study brings significant insights into this research topic, it also has several limitations. Firstly, as our research examined the coauthor state among team members based on a given period, it is unable to reveal the dynamic state of co-author networks. Future research can be done from a comparative study of coauthor state in different periods to reveal how changes in networks affect the performance of team knowledge creation. Next, the use of coauthored publications to track network membership in our study reflects the members' interactions to some extent, yet fails to reflect tacit communication completely. Scholars may conduct their future studies with the combination of interview and questionnaire to provide deeper insights. Moreover, the research indexes selected in our study is relatively limited. In the context of enough samples and with the ability to overcome the difficulty in obtaining resources, future studies can make a more comprehensive investigation on knowledge creation performance by adopting more network indexes and by combining non-network index factors drawn from previous research. Furthermore, the inferences made about managerial implications are a bit of a stretch, as this study cannot really tell us much about creative process caused by tie stability. The implications should focus more tightly on what this might cause about academic publishing and networks of authors who publish together frequently. For example, the mediators of the relationship between tie stability and team knowledge creation are worth to be investigated in future research. Last, it should be acknowledged that 71% of the sample was Male. This seems extraordinary, particularly in the domain of human resource management. Thus, randomness of this sample must be reconsidered in the next study.

AUTHOR CONTRIBUTIONS

ML contributed in finishing the first draft. XZ revised this paper. PZ and WL contributed to this research by giving suggestions and involved in data collection.

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METHODS
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Hypernetworks Reveal Compound Variables That Capture Cooperative and Competitive Interactions in a Soccer Match

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The combination of sports sciences theorization and social networks analysis (SNA) has offered useful new insights for addressing team behavior. However, SNA typically represents the dynamics of team behavior during a match in dyadic interactions and in a single cumulative snapshot. This study aims to overcome these limitations by using hypernetworks to describe illustrative cases of team behavior dynamics at various other levels of analyses. Hypernetworks simultaneously access cooperative and competitive interactions between teammates and opponents across space and time during a match. Moreover, hypernetworks are not limited to dyadic relations, which are typically represented by edges in other types of networks. In a hypernetwork, *n-ary* relations (with $n > 2$) and their properties are represented with hyperedges connecting more than two players simultaneously (the so-called *simplex*—plural, *simplices*). Simplices can capture the interactions of sets of players that may include an arbitrary number of teammates and opponents. In this qualitative study, we first used the mathematical formalisms of hypernetworks to represent a multilevel team behavior dynamics, including micro (interactions between players), meso (dynamics of a given critical event, e.g., an attack interaction), and macro (interactions between sets of players) levels. Second, we investigated different features that could potentially explain the occurrence of critical events, such as, aggregation or disaggregation of simplices relative to goal proximity. Finally, we applied hypernetworks analysis to soccer games from the English premier league (season 2010–2011) by using two-dimensional player displacement coordinates obtained with a multiple-camera match analysis system provided by STATS (formerly Prozone). Our results show that (i) at micro level the most frequently occurring simplices configuration is 1vs.1 (one attacker vs. one defender); (ii) at meso level, the dynamics of simplices transformations near the goal depends on significant changes in the players' speed and direction; (iii) at macro level, simplices are connected to one another, forming "simplices of simplices" including the goalkeeper and the goal. These results validate qualitatively that hypernetworks and related compound variables can capture and be used in the analysis of the cooperative and competitive interactions between players and sets of players in soccer matches.

Keywords: network theory, hypernetworks, network dynamics, performance analysis, soccer

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INTRODUCTION

Coaches, players, and scientists have long tried to understand team behavior dynamics during a game, aiming to develop interventions and training plans that may increase team performance (Araújo and Davids, 2016; Passos et al., 2017). Broadly speaking, research in performance analysis in team sports searches for variables describing game dynamics that are: (i) useful and accessible to coaches and athletes; (ii) obtained automatically or semi-automatically from game observation; and (iii) related to team outputs, such as, match results. For finding such variables it is necessary to capture the multi-leveled dynamics emerging from differential interactions between many heterogeneous parts (e.g., players), while considering potential adaptations to changing environments. In this way, teams and athletes can be seen as co-evolving subsystems that self-organize into new structures and behaviors (Johnson, 2013), i.e., they form team synergies (Araújo and Davids, 2016). Such team synergies emerge from physical and informational constraints (Schmidt et al., 1998, 2011). Importantly players are perceptually linked mainly by informational constraints, since physical links among them are very rare (e.g., when forming a wall of players; Riley et al., 2011). Several studies have analyzed the coupling among performers based on interpersonal distance measures (Passos et al., 2011; Fonseca et al., 2013; Rio et al., 2014), with a higher emphasis on the distance between a player and the immediate opponent (e.g., Headrick et al., 2012). In the present study, we extend this player-immediate opponent distance to the closest player (opponent or not).

These interactions, based on informational and physical constraints have been studied by network theorical approaches, like social network analysis (SNA). SNA is a powerful tool to capture and study interpersonal relations in team sports (Araújo and Davids, 2016); however, this method can only be used for representing binary (*2-ary*) relations (Johnson, 2006; Criado et al., 2010; Boccaletti et al., 2014). The most common graphical representations of SNA depict players as nodes in fixed positions in the pitch (the field of the match), with edges between them representing the cumulative "ball flux," i.e., ball passes, over time (Duch et al., 2010; Fewell et al., 2012; Grund, 2012; Clemente et al., 2015; Araújo and Davids, 2016; Travassos et al., 2016). This is a fundamental limitation of typical SNA in sport context, as it restricts its application to the attacking phase of team dynamics. Typically, all other relevant types of interactions, either cooperative or competitive, are not considered. In this study, we investigate how cooperative (e.g., between players of the same team in order to create a scoring opportunity) and competitive interactions (e.g., between players of different teams competing for ball possession) may be captured and analyzed via multilevel hypernetworks. On the one hand, according to Boccaletti et al. (2014), multilevel networks constitutes the new frontier in many areas of science since it describes systems that are interconnected through different categories of connections (e.g. relationship: teammate vs. opponent; activity: increasing vs. diminishing interpersonal distance; category: attacker vs. midfielder) that can be represented in multiple layers, including networks of networks (e.g., interactions between teams). On the other hand, in a hypernetwork, a hyperedge can connect more than two nodes, thus directly representing *n-ary* interactions occurring among small sets of nodes, $\langle p_i, \ldots, p_j \rangle$ (Johnson, 2006, 2008, 2013, 2016; Criado et al., 2010; Boccaletti et al., 2014). This generalization provided by hypernetworks enables the representation of cooperative and competitive interactions that occur during the game and that involve an arbitrary number of players (teammates or opponents).

In the present study, we have extended the approach by Johnson and Iravani (2007) by introducing compound variables, e.g., local dominance, which capture the structure and dynamics of cooperative and competitive interactions in the following ways:

i. By considering the domain specificity of soccer matches to tag the sets of players formed (e.g., 2 vs. 1 corresponds to a set with two attackers and one defender) as these tags describe local dominance (Duarte et al., 2012);
ii. By including the spatiotemporal occurrence of the different sets of players by counting their frequency and location;
iii. By analyzing and relating the dynamics of the sets with players velocity in specific events (goal scoring opportunities);
iv. By studying, for the same events of interest, the formation and dynamics of higher level simplices; notably, the relations between simplices of simplices.

The present approach is applied to a set of matches in order to investigate how the proposed compound variables can be useful on characterizing the behavior of players and teams at different levels and the relationships between these levels and match context, e.g., team local dominance and current match result.

As a first step in this approach, it is necessary, at each level of analysis, to identify the meaningful relations for the match dynamics, and represent them using different criteria for selecting the players in each set (i.e., connected by a hyperedge; Johnson, 2008, 2016). According to Passos and colleagues the analysis of the interpersonal distances is adequate for complex systems modeling (Passos et al., 2011). As we are interested in cooperative and competitive behavior in the pitch, geographical proximity between players (Headrick et al., 2012) can capture whether an interaction between players exists or not (e.g., functional couplings). Also, in the investigation of the relation between higher (macro) level of analysis and players' individual actions (micro), it is important to consider the velocity of each player, as well as the velocity of the set of players, represented by the set's geometric center and obtained through the computation of each players' velocity. For example if such set is expected to maintain its structure or if it is about to split when a player's velocity vector is moving away from the other players. Operationally, we have defined that a player does interact with his closest player; this interaction is cooperative when that closest player is a teammate, and competitive when it is an opponent. Thus, time and space are highlighted in the present approach using hypernetworks because it uses geographical proximity criteria, and also because it captures temporal changes, by considering the players' geographical positions over time

$(t_1, t_{2,\ldots}, t_n)$. The compound variables adopted in this study reflect and capture this space and temporal features, e.g., local dominance and the dynamics, i.e., changes on, players' sets.

In **Figure 1**, we show an example of a set of nodes identified at Level N: two attacking players (a_1 and a_2,), a defender (d_1), a goalkeeper (d_0), and a goal (G_a). These nodes are connected by two hyperedges at Level $N + 1$, corresponding to sets $\langle a_1, a_2, d_1 \rangle$ and $\langle d_0, G_a \rangle$ in one time frame, and $\langle a_1, d_1 \rangle$ and $\langle a_2, d_0, G_a \rangle$ on the next.

For a more complete description of the system's dynamics, each tuple identified in the hypernetwork can be extended by an element, R, that describes the relationships in the set (Johnson, 2013). Each of these extended sets is called a *simplex* (Johnson and Iravani, 2007; Johnson, 2013). For example, R is the path to understand why the sets $\langle a_1, a_2, d_1 \rangle$ and $\langle d_0, G_a \rangle$ on one frame lead to the sets and $\langle a_1, d_1 \rangle$ and $\langle a_2, d_0, G_a \rangle$ on the next. When a player observes the game searching for the best action possibilities offered by the other players' positioning, the entire configuration of team-mates and opponents has to be perceived. Such sets of players, either in 1vs.1, 2vs.1, or 2vs.2, or any other set, may be related to one another, regarding the players' general configuration. Thus, when one player decides to move, the entire configuration is affected. Johnson and Iravani (2007) propose naming the "2 attackers vs. 1 defender" structure, the *defenders' dilemma*, since the defenders can opt to tackle the ball or intercept the pass between attackers. In a similar situation involving the goalkeeper, the *goalkeepers' dilemma*, the options are moving to the right or left of the goal, or moving toward the attacker leaving the goal behind. The goal can therefore be considered as a constraint that attracts the opponents and instigates the defenders to position as if it were an opponent. For this reason, we have included goals in the definition of simplices, because they show similarities to an "attacking player" (e.g., in the goalkeepers dilemma).

In this study, we propose several compound variables to describe the players' cooperative and competitive behavior dynamics during a soccer match. The simplest of these variables depicts the dominant interactions in each set, and is expressed by two values representing the number of attacking and defending players, for example, 2 vs. 1 corresponds to a set with two attackers and one defender. In **Figure 1**, the two dominant relationships are $R_1 = (2\ vs.1)$ and $R_2 = (0\ vs.1)$, and the corresponding simplices are $\sigma_1 = \langle a_1, a_2, d_1; (2\ vs.1) \rangle$ and $\sigma_2 = \langle d_0, G_a; (0\ vs.1) \rangle$. The behavior of a team during a match can then be described by other compound variables that characterize the relative frequencies of the aforementioned relationships. For example, the minimal structure (simplex) of players' interactions occurring more frequently in a match can be assessed.

At higher complexity levels, the hypernetwork can represent the interactions between related simplices, or simplices of simplices (see **Figure 1**, *Level N + 3;* Johnson, 2006, 2013; Johnson and Iravani, 2007). In what regards the study of dynamics: less dynamic structures (e.g., number of players, players' roles, etc.) are called *backcloth*, and higher rate changes

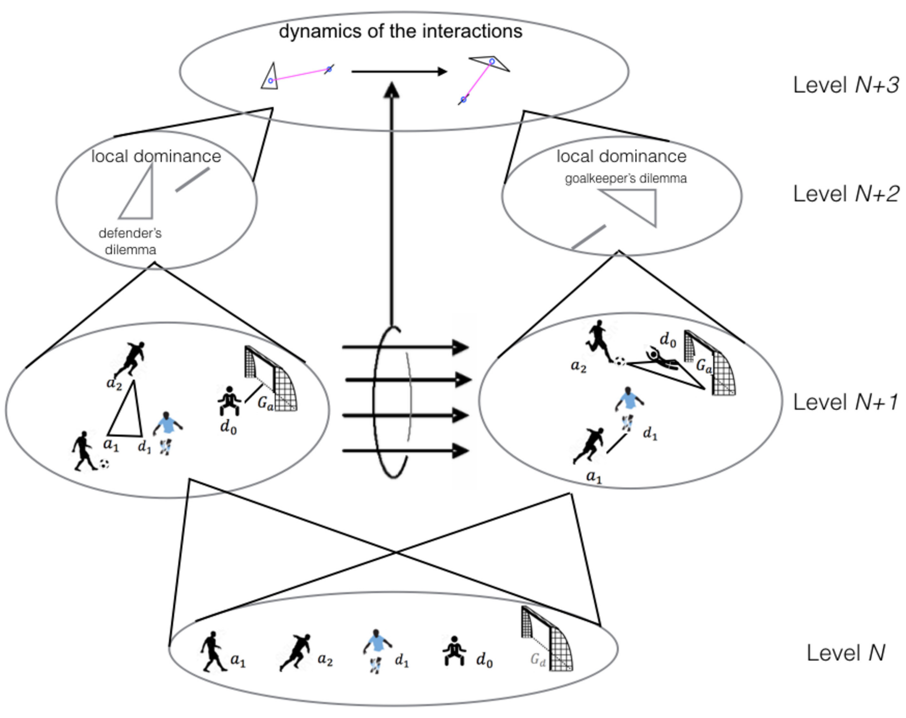

FIGURE 1 | Multilevel hypernetwork representation (from bottom to top). Each level corresponds to a different abstraction level (Level N, players in the pitch; Level $N + 1$, proximity-based simplices; Level $N + 2$, local dominance relation; Level $N + 3$, dynamic analysis via simplices of simplices). Also represented, the displacement in a soccer game of 2 sequential time frames (from the left to the right hand side) (Adapted from Johnson and Iravani, 2007).

(e.g., players positioning in relation to opponents, teammates and the goal or the ball) are called *traffic* (Johnson, 2013) and represent dynamics within the backcloth. Thus, one important feature of hypernetwork analysis in the sports context is the representation of players' *moves,* across time and space, and between structured sets (i.e., from one simplex to another). As shown in **Figure 1**, this multilevel approach allowed us to capture the number of players and their moves and the players in the match-day squad (*Level N*), the coordinated sets of players along the match (*Level N + 1*), the local advantage of one team over the other (e.g., numerical dominance; *Level N + 2*), and the relationship between the sets (*Level N + 3*). Moreover, by using this approach different compound variables, e.g., local dominance, may explain distinctive aspects of the competitive and cooperative behavior of players and teams.

In this study we put forward the hypothesis that hypernetworks and compound variables over these hypernetworks can capture relevant features of soccer team dynamics during a match. We validate qualitatively this hypothesis by applying the proposed method to a set of matches of a focal team within different contexts and by analysis the results thus obtained. The aim of this study was therefore to operationalize a method addressing different levels of hypernetworks on soccer matches and by providing a study case for tackling the following questions:

i. At *Level N*: Has the backcloth (players) changed during the match, as expressed by events such as, substitutions, sent-offs and injuries? Typical notational analyses answer this question directly.

ii. At *Level N + 1*: What are the most frequently occurring simplices in soccer matches? A histogram with the relative frequencies of occurrence of every type of simplices (e.g., 1vs.1, 2vs.1...) can be computed.

iii. At *Level N + 1*: Are there any differences in simplices' structure and occurrence between home or away matches for Team A? A heat map (2D spatial frequency map) for each of the relationships can be computed to show their location in the pitch.

iv. At *Level N + 1*: Are there any changes in simplices structure and field position as the match score changes? Instead of considering the entire match, the heat maps can address specific periods of the match. These periods are bounded by relevant match events, e.g., a goal being scored.

v. At *Level N + 2*: What are the dynamics of the simplices' interactions near the goal, immediately before the score changed? Instead of examining the results for the entire match, or for given periods, it is possible to perform a frame-by-frame analysis to assess which simplices formed and how they changed, and also to identify the players who contributed to those changes.

vi. At *Level N + 3*: Is there any interaction between simplices leading to the emergence of new team configurations that, in turn, can lead to scoring a goal? To answer this question, it is necessary to evaluate how the different simplices relate to one another, how they aggregate into higher-level simplices, and how they recombine into different simplices.

METHODS AND MATERIALS

Five matches were analyzed from a pool of 11 matches of the English Premier League season 2010–2011 provided by STATS (formally Prozone). This data set was selected because it contained no errors, such as, missing or duplicated positioning data, and because the *backcloths* were equivalent (i.e., there were no differences between teams regarding the number of players due to sent-offs or injuries without substitutions). Participants included all the players in the field from Team A (our focal team), and the players from five teams playing against team A (teams B, C, D, E, and F). The matches included three home matches, against teams B, C, and D, and two away matches, against teams E and F. The players' substitutions were considered but not analyzed in detail in this study (i.e., data for both initial squad and substitutes are used but the implications of substitutions in the backcloth are not taken into consideration).

Matches and their score were: Team A vs. Team B (1–0); Team A vs. Team C (1–0); Team A vs. Team D (1–0); Team E vs. Team A (2–1) and Team F vs. Team A (0–0). The details for each match are presented in **Table 1**.

For each match, raw data consisted of two-dimensional player displacement coordinates provided by STATS. These data were obtained by a multiple-camera match analysis system whereby the movements of the 22 players during the match were recorded with eight cameras positioned at the top of the stadium. The frames were processed at 10 Hz through an automated system that synchronized the video files. The effective playing area was 80 m wide and 120 m long, including the out-of-bound locations such as, set-plays. A computer procedure for computing the simplices' hyperedges set with the proximity criterion was implemented using GNU Octave version 4.2.0 and applied to each frame. This criterion has the advantage of being non-parametric; the corresponding pseudo-code for this algorithm is provided in **Figure A1**.

Each simplex was represented graphically by the convex hull computation (the minimum convex area containing all players in the simplex) and included the velocity of each player (vector velocity considering the instant *t-1* and *t*), as well as the velocity of the geometric center of the simplices.

To represent the field positioning of the different types of simplices, we used heat maps for the frequency of simplices occurrence. This type of graphical representation allowed us to capture the most frequent type of simplices for each time period, as well as their geographical position in the field.

TABLE 1 | Matches' details indicating the result and changes in the team structure due to sent-offs, substitutions, or injuries (without substitution).

Matches	A vs. B	A vs. C	A vs. D	E vs. A	F vs. A
Results	1–0	1–0	1–0	2–1	0–0
Substitutions	3–3	3–3	3–3	3–3	2–2
Sent-offs	0–0	0–0	0–0	0–0	1–1
Injuries (without substitution)	0–0	0–0	0–0	0–0	0–0

For analyzing specific time points, we represented simplices (*Level N + 2*, **Figures 5**, **6**) with two different colors: for players in team A, vertices are in **red**, for players in team B, vertices are in **green**. For the higher-level simplices in level *N + 3*, **Figure 6**, the blue **o** symbol represents the geometric center of the simplices. Such representation facilitates the simultaneous identification of players in both teams and the type of simplices in level *N + 3*. Moreover, we also represented the proportion (local dominance or balance) of each type of simplices in level *N + 2*, as well as the type of relation that exists between the simplices, or simplices of simplices in any instant of time at level *N + 3*. The velocity of the simplices and players were also included, thus allowing for the evaluation of simplices consistency, for example, transformations such as, when a player entered or moved away from a given simplice, or when all players moved simultaneously to the same position, could be detected.

RESULTS

Our results revealed how the matches' hypernetworks are characterized from *Level N* to *Level N + 3*.

We analyzed the structure at *Level N* of the five matches. As expected, we found 11 players in each team, with some players being substituted but with no sent-offs (with the exception of match F vs. A) or injuries occurring after there were no substitutions left (hence the total number of players remained constant). At this level of analysis, individual player statistics and heat maps of their positioning during the match are usually performed. However, as this type of performance analysis is widespread in sport (for a review see Passos et al., 2017), and given that the focus of this paper is on team behavior, we do not present such results here.

We computed the relative frequencies of the simplices structures at Level *N + 1* for players in both teams (**Figure 2**). The most frequently occurring simplices structures in the 5 matches: 1vs.1; 2vs.1; 1vs.2; 2vs.2; 3vs.1; 1vs.3. These results reveal that the most frequently occurring simplices structures are similar in every match. Around 25% of the simplex structures corresponded to 1vs.1, independently of the type of match (home or away) or its final result. The second most frequently occurring simplices structures were 2vs.1 and 1vs.2 (around 10%), followed by 2vs.2 (around 6%), and finally by 3vs.1 and 1vs.3 (around 3%). Among other simplices structures, we could also often find interactions between the goalkeeper and the goal, as identified in 0vs.1 or 1vs.0 structures (around 11%). However, these simplices structures do not reveal a social interaction (i.e., cooperation or competition) and are therefore not compared to other structures.

By computing the frequencies for the "local dominance tag" compound variable it is possible to investigate for each game the most frequent cooperation and competition interactions sets.

Level N + 1 describes the geographical distribution in the pitch of the most frequently occurring simplices structures, as shown in *heat maps* (**Figure 3**).

Figure 3 shows that although 1vs.1 is the most frequently occurring simplex tag in every match, the location in the pitch where it can more often be found varies between matches. Simplices, 2vs.1, indicating simultaneous cooperation and competition, occurs mostly in the mid-field, and simplices 1vs.2 occurs mostly in the opponent side of the field.

By identifying the relevant events in a match, such as, changes in the score, at *Level N + 1* we can capture changes in collective behavior across time. **Figure 4** shows the results of this analysis in heat maps corresponding to different sections of the E vs. A match (final result 2–1). For example, these heat maps reveal that

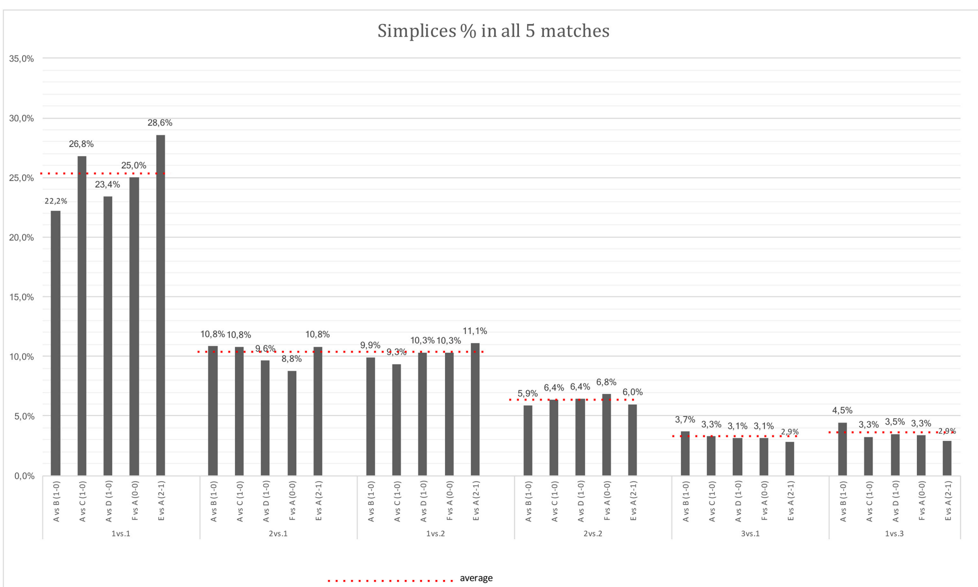

FIGURE 2 | Histogram for the most frequently occurring simplices structures in the 5 matches: 1vs.1; 2vs.1; 1vs.2; 2vs.2; 3vs.1; 1vs.3. The matches (and score) were: Team A vs. team B (1–0); Team A vs. Team C (1–0); Team A vs. Team D (1–0); Team E vs. Team A (2–1); and Team F vs. Team A (0–0).

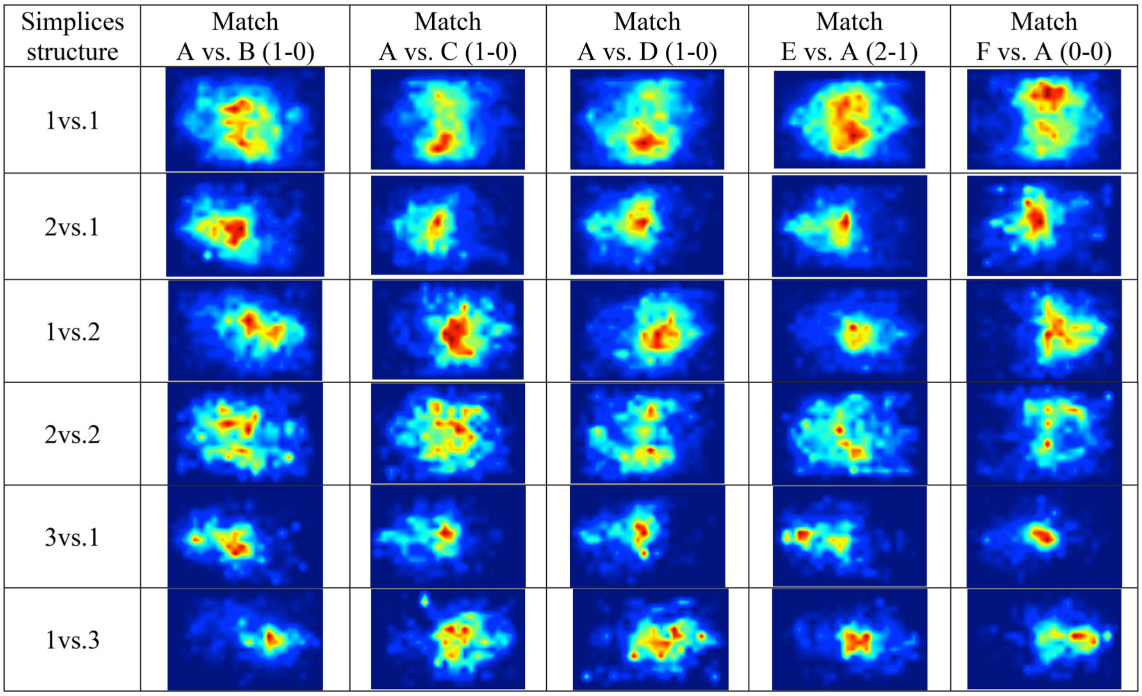

FIGURE 3 | *Heat maps* for field position of the most frequent simplices structures during the matches (when Team A, playing at home, attacks are represented from left to right). The color gradient from red to blue represents the frequency of simplices in that location (from most frequent, red, to not occurring, dark blue).

the team with the lowest score shows a tendency for a decrease in frequency of 2vs.2 near its own goal. Moreover, the next most frequently occurring simplices, 3vs.1 and 1vs.3, can be found more often close to the goal of the wining team.

Level $N + 2$ captures simplices dynamics, for example, before changes in the score. Here we present an analysis of the simplices having their geographical center closer to the goal. To answer the question "what creates an opportunity for the attackers to score?" simplices reveal how the defenders' local dominance is broken by the attackers. **Figure 5** shows an example of local dominance, in which team A (playing at home against B) scores in a counter-attack sub-phase. The play was analyzed in a set of consecutive frames (at 1 Hz) that captured the simplices nearer the goal of interest. A velocity vector computed using consecutive frames was associated to each player to show aggregation or disaggregation, as a player moved toward or away from the simplices geometric center.

The example in **Figure 5** shows that, in the frames before a goal is scored, some attacking players (e.g., 6, 7, and 10) increase their speed to place themselves in a better position either to create an invitation for a successful pass or to create a scoring opportunity. On the other hand, defensive players try to maintain or reduce interpersonal distance (e.g., 16, 19, and 22). This is aligned with other studies (Fonseca et al., 2013) where it was observed that attackers tried to increase the interpersonal distance while the defenders tried to reduce it. The consequence of these moves can be captured by simplices' configuration. This is more evident if a player stays in the same simplex or moves to another simplex. Changes in players' velocity leads to break (disaggregate) or maintain (aggregate) the simplex's integrity when they move away or toward the simplex geometric center, respectively.

Level $N + 3$ indicates how simplices interact between them, thereby creating higher-order simplices. These simplices form by aggregation of Level $N + 1$ simplices based on the proximity criterion of their geographical centers (**Figure 6**). To uncover the changes in simplex structures leading to goal scoring, higher-order simplices (**Figure 6**, purple polygons) were analyzed for the frames where significant changes occurred in the Level $N + 3$ structures (simplices of simplices).

The example of *Level* $N + 3$ analysis in **Figure 6** also reveals the connections between players before a goal was scored. The simplex formed by the goalkeeper and the goal is connected with other simplices, as the goalkeeper tries to align with the closest simplice while maintaining the link with the goal. **Figure 6** also shows how the simplices furthest from the goal are connected with simplices more directly involved in the attacking phase (i.e., closest to the goal). Other information that can be extracted from *Level* $N + 3$ is how fast changes in the link with the goal can occur, and which simplices are "disconnected," for example, on one side of the field.

DISCUSSION

The different levels of analysis of a hypernetwork can capture various degrees of team behavior dynamics, from player, to simplices, and to interactions between simplices across space and time.

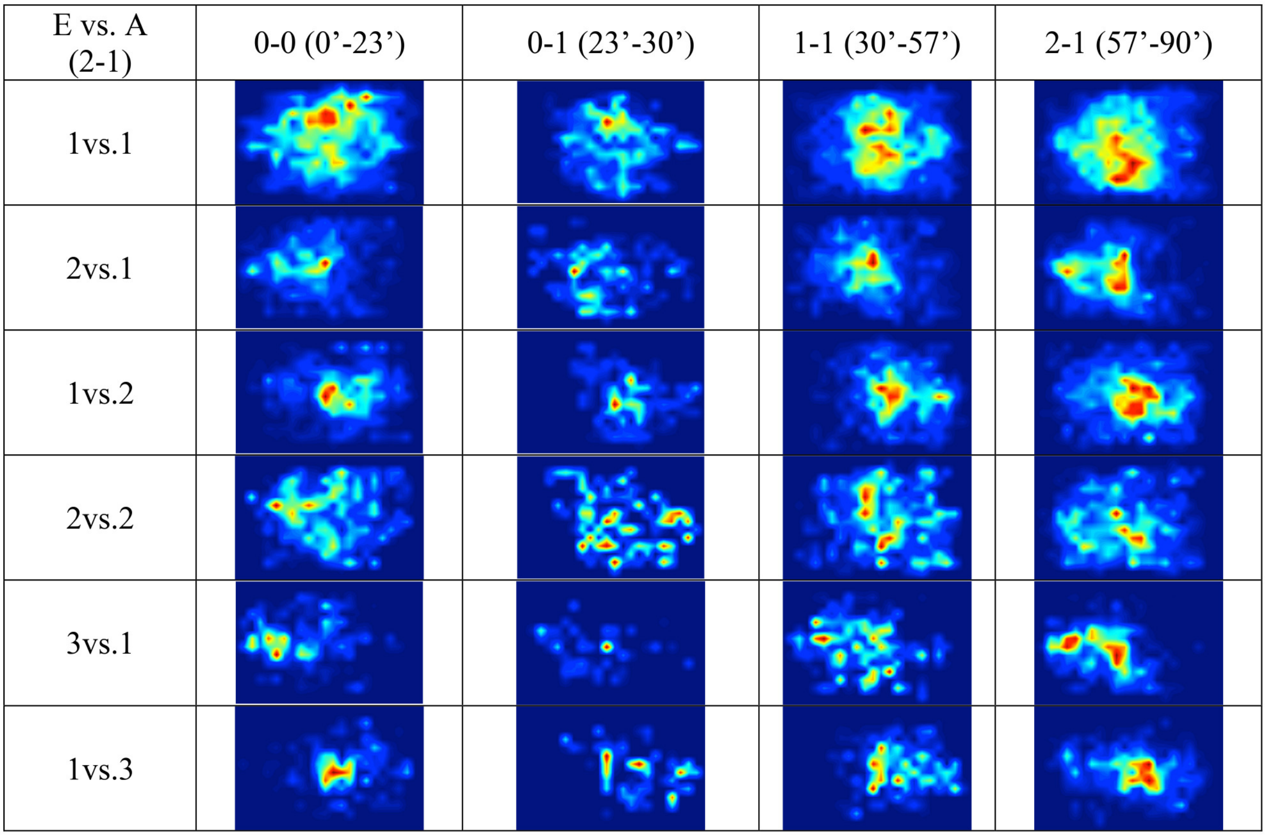

FIGURE 4 | *Heat maps* for the field position of the different simplices structures (visiting team A attacks from the right to the left hand-side). Each column corresponds to a temporal section of the match bound by a score change. The color gradient from red to blue represents the frequency of simplices in that location (from most frequent, red, to not occurring, dark blue).

At *Level N + 1*, we could identify the types of simplices occurring more often in a match, independently of their score or context (home or away). The most frequently occurring simplex was 1vs.1, followed by 1vs.0 and 0vs.1. The latter represents the link between the goalkeeper and the goal. Also occurring frequently were simplices with an unbalanced number of players, 2vs.1 and 1vs.2 (~10%), followed by the 2vs.2 simplices (~6%), and finally by the 3vs.1 and 1vs.3 simplices (~3%).

Important interpretations can be inferred from the simplices at *Level N + 1* when space and time, or contextual variables (home or away match) are considered. For example, team A won three home matches (all with score 1–0) but tied (score 0–0) or lost (score 2–1) in away games. The 1vs.1 simplices tend to occur in the mid-field and on the right of the attacking direction of team A (**Figure 3**). However, in the match lost against team E, 1vs.1 simplices were more dispersed and toward the left side of the pitch. Another frequently occurring simplex with a balanced number of players was 2vs.2, for both teams (**Figure 3**). Interestingly, these simplices also had a unique distribution in the match lost against team E, as they occurred more toward the center of the pitch and the opponent middle field. Additionally, these structures differed from match to match, showing the emergent properties of complex adaptive systems, specifically the context dependency (opponents and scoring evolution; Araújo and Davids, 2016).

Concerning simplices with an unbalanced number of players, 2vs.1 occurred more often in the center of the pitch and in the opponent middle field (similarly to 2vs.2 in the match lost against team E). The 1vs.2 simplices were also detected more often in the middle fields. Simplices 3vs.1 were distributed in the center of Team A's middle field, however, in the match against team E, they were more distant from their own goal (in the middle field). In the opposite way, in the matches against teams B and F, there were some notable occurrences of 3vs.1 simplices near team's A goal. Moreover, in these matches, 1vs.3 occurred near the center but more toward team A's middle field, suggesting that team B and F "forced" team A players away from their goal.

The results obtained considered both geographical placement and context dependency, and showed that the use of simplices formation captured match properties, such as, local dominance. These properties emerge in each match event resulting from the local interaction between players of both teams. Multilevel hypernetworks proved to be a useful method in answering to chief problems such as, the relation among micro (e.g.,

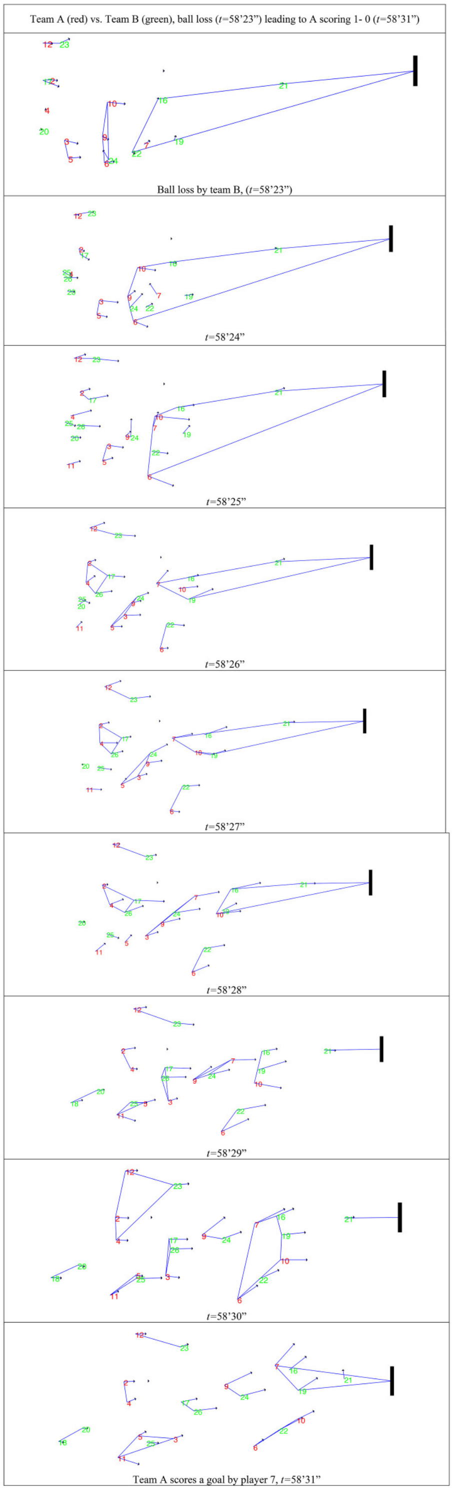

FIGURE 5 | Simplices in a sequence of nine frames (58′23″ to 58′31″) leading to a goal by Team A. Visiting players are attacking from right to left (represented in green), while home players are attacking from left to right (represented in red, including the opponents' goal). A simplex is represented by the polygon (or a line when there are only two players) defining the convex hull (or envelope) that links the nodes (players or goal). A velocity vector for each player is also presented.

players' positions), meso (e.g., local dominance), and macro levels (e.g., match result). Moreover, the use of hypernetworks allows that the analysis can consider more than the typical (in SNA) *2*-ary relations between players. These contributions fulfill previous gaps in interpersonal coordination research (Passos et al., 2016).

The analysis of the dynamics of simplices interactions at *Level N + 2* revealed abrupt changes in the speed and direction of player vectors near the goal. These changes showed a tendency to be associated with transformations in simplex structure, for example, when an attacker passed through the defenders to score, or when a player disconnected from one simplex to interact with another (to balance or unbalance the simplex). The example in **Figure 5** analyzed a change in the score that resulted from a ball lost by team B in team A's middle field that led to a successful counter attack (with a goal scored). This event was characterized by transformations in the simplices' structure occurring within the short duration of the counter attack (9 s, from 58′23″ to 58′31″). Next we present the set of simplices (σ) and their evolution for these 9 s leading to a goal being scored by Team A (at 58′31″). Simplices containing the player who scored the goal are identified with (S). Simplices containing the goal are identified with (G).

$$\sigma_{1,\,58'23''}\langle a_3,\ a_5\rangle + \sigma_{2,\,58'23''}\langle a_9,\ a_6, a_{10}, d_{24}\rangle + \sigma_{3,\,58'23''}\langle a_7,\ d_{22}, d_{16}, d_{19}, d_{21};\,(G,S)\rangle$$

$$\sigma_{1,\,58'24''}\langle a_3,\ a_5\rangle + \sigma_{2,\,58'24''}\langle a_9,\ a_6, a_{10}, d_{24}, a_7,\ d_{22}, d_{16}, d_{19}, d_{21};\,(G,S)\rangle$$

$$\sigma_{1,\,58'25''}\langle a_3,\ a_5\rangle + \sigma_{2,\,58'25''}\langle a_9,\ d_{24}\rangle + \sigma_{3,\,58'25''}\langle a_6, a_{10}, a_7,\ d_{22}, d_{16}, d_{19}, d_{21};\,(G,S)\rangle$$

$$\sigma_{1,\,58'26''}\langle a_3,\ a_5, a_9,\ d_{24}\rangle + \sigma_{2,\,58'26''}\langle a_6,\ d_{22}\rangle + \sigma_{3,\,58'26''}\langle a_{10}, a_7,\ d_{16}, d_{19}, d_{21};\,(G,S)\rangle$$

$$\sigma_{1,\,58'27''}\langle a_3,\ a_5, a_9,\ d_{24}\rangle + \sigma_{2,\,58'27''}\langle a_6,\ d_{22}\rangle + \sigma_{3,\,58'27''}\langle a_{10}, a_7,\ d_{16}, d_{19}, d_{21};\,(G,S)\rangle$$

$$\sigma_{1,\,58'28''}\langle a_3,\ a_7, a_9,\ d_{24};\,(S)\rangle + \sigma_{2,\,58'28''}\langle a_6,\ d_{22}\rangle + \sigma_{3,\,58'28''}\langle a_{10},\ d_{16}, d_{19}, d_{21};\,(G)\rangle$$

$$\sigma_{1,\,58'29''}\langle a_3,\ d_{17},\ d_{26}\rangle + \sigma_{2,\,58'29''}\langle a_9, a_7,\ d_{24};\,(S)\rangle + \sigma_{3,\,58'29''}\langle a_6,\ d_{22}\rangle + \sigma_{2,\,58'29''}\langle d_{21};\,(G)\rangle$$

$$\sigma_{1,\,58'30''}\langle a_3,\ d_{17},\ d_{26}\rangle + \sigma_{2,\,58'30''}\langle a_9,\ d_{24}\rangle + \sigma_{3,\,58'30''}\langle a_6, a_7, a_{10}, d_{16}, d_{19},\ d_{22};\,(S)\rangle + \sigma_{2,\,58'30''}\langle d_{21};\,(G)\rangle$$

$$\sigma_{1,\,58'31''}\langle a_9,\ d_{24},\rangle + \sigma_{3,\,58'31''}\langle a_6, a_{10},,\ d_{22}\rangle + \sigma_{2,\,58'31''}\langle a_7, d_{16}, d_{19}, d_{21};\,(G,S)\rangle$$

The results show that certain moves performed by the player who scored the goal (player a_7) had significant impact on some simplices transformations, for example, at instants 58′27″, 58′28″, 58′29″, 58′30″, and goal scored. Player a_{10} had an important role in promoting balance in the simplex that scored the goal (with player a_7), by maintaining defender d_{19} distant from his teammate d_{16}. Moreover, player d_{19} appeared to be facing the defender's dilemma, hesitating between defending his opponent (player a_{10}) and supporting his teammate (player d_{16}). Player d_{24} was also essential in the attack play leading

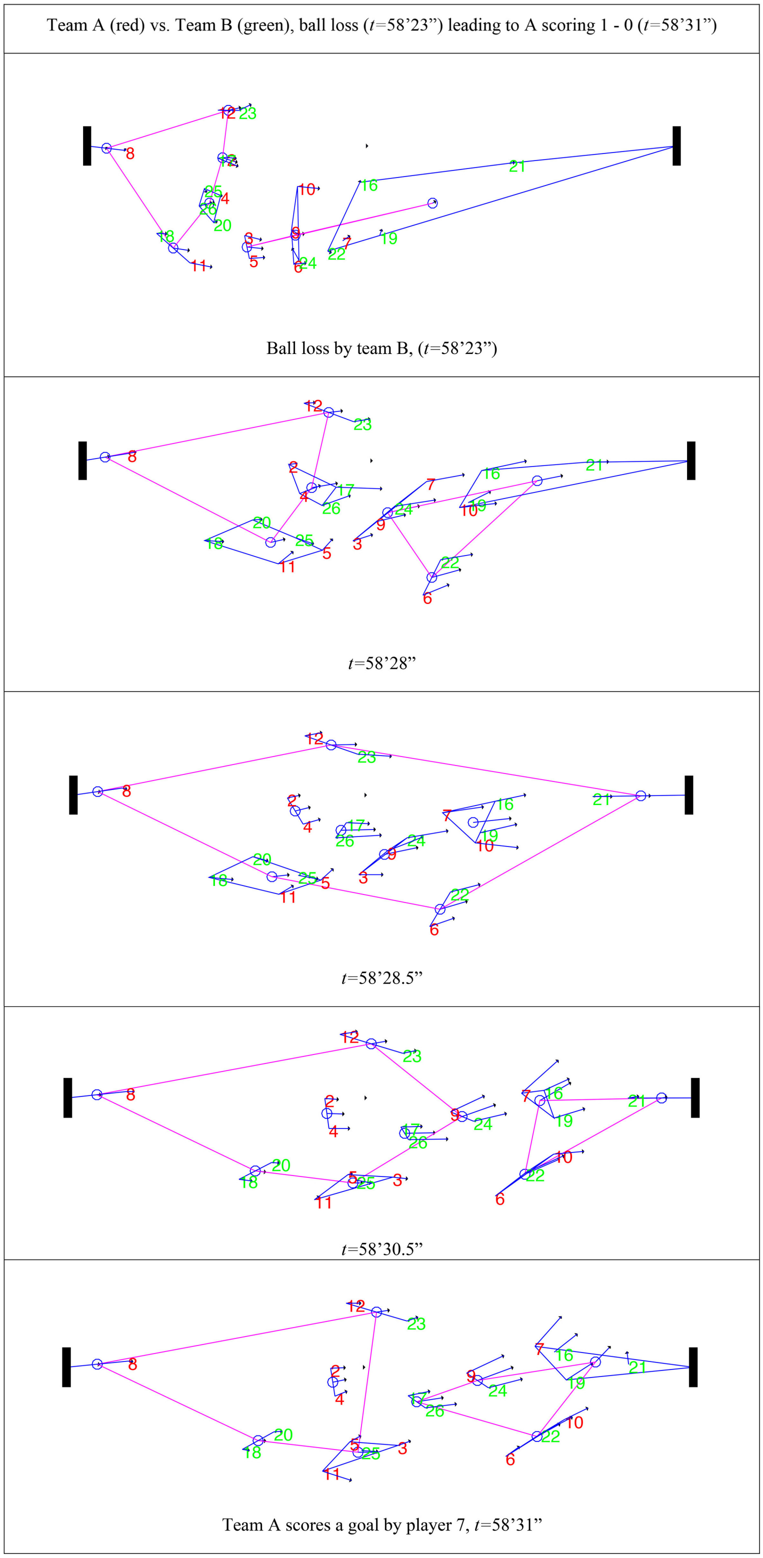

FIGURE 6 | Higher-order simplices (simplices of simplices) in a sequence of five frames before team A scores a goal. Higher-order simplices are represented by the polygon (and lines) forming the convex hull (–) that connects the geographical centers of the $N + 1$ simplices. See **Figure 5** legend for the codes for players, their velocity, and simplices.

to the goal scored, as he lost the ball but kept pursuing it, almost reaching player a_7 and thereby including him into his simplex. Finally, player a_6 broke the central simplex (containing teammate a_7) by attracting a defender toward him and hence reducing the number of players in the central middle field.

Results showed that by considering the temporal sequence of simplices transformations during critical events of the match (e.g., from ball recovery to scoring a goal) the dynamics of interaction among players is captured. Moreover, it is possible to analyze how interactions among players led to changes in simplices' structures and, consequently to such critical events (e.g., a goal scoring opportunity). Multilevel hypernetworks offer a fine temporal grain of analysis of how the micro-meso-macro level relationships emerge.

Level N + 3 clarified the dynamics of team behavior by considering the entire set of simplices, including the interactions between them (which form simplices of simplices). This level of analysis revealed the connections of players with simplices during a match. We found that the goal has an "anchoring effect" toward the goalkeeper, however, this simplex also connected with the nearer simplex (0vs.1 represents the home team and 1vs.0 the visiting team). Some simplices seemed to disconnect during critical situations, for example, when other simplices were close to the goal. This may be explained by an intentional reduction in speed by the attacking players to try and maintain the nearest defenders away from teammates (**Figure 6**).

This study showed that the hypernetworks' analysis by considering simplices of simplices reveal the degree of connection between sub-sets of players.

CONCLUSIONS AND LIMITATIONS

We have applied multilevel hypernetworks analysis, and a set of associated compound variables, to selected soccer matches by using positional variables for all players involved.

The interactions between players, as well as the sets of these interactions (simplices), were assessed based on interpersonal distance, more specifically *spatial proximity* and *instant speed* relational variables. Each player is therefore linked to his closest player (or goal, for the goalkeeper) and at higher levels, simplices are also linked to their closest simplices. The vectors representing the players' speed can represent the emergent moves from the players in order to search for new interactions or escape from others. These two "interaction variables" allowed for a deeper analysis of the structures and coordination levels emerging from the game.

Our results revealed a pattern in these interactions' dynamics that was independent of the type (home or away) and score of the match. Specifically, in every match analyzed the most frequently occurring simplices structures were, by decreasing order of frequency, 1vs.1, 2vs.1 and 1vs.2, 2vs.2, and finally, 3vs.1 and 1vs.3.

However, these simplices show differences in their distribution on the pitch, and this is particularly evident for unbalanced simplices such as, 2vs.1, 1vs.2, 3vs.1, and 1vs.3. These differential distributions are consistent with the match result (wins vs. losses) and the opponent team's strength.

We analyzed the changes in local dominance at *Level N + 2* associated with critical events (e.g., score changes) and found that dramatic speed changes can be detected in the players of simplices directly linked to the event (goal scored). Velocity is therefore the variable that allows players to improve their positioning to score or to unbalance the situation.

Finally, our last and global analysis level revealed how all the simplices were connected, but most importantly, it enabled to permanently connect all the simplices into larger hypersimplices, including the goal and goalkeeper simplex, and also the defenders and attackers who were distant from the goal.

These results may significantly contribute to improve training and playing strategies. We highlight the importance of mastering 1vs.1 situations (with and without the ball), as this structure occurs more frequently in all types of matches. For example, coaches could design exercises to train players to rapidly transform any structure into a 1vs.1 structure. Unbalanced situations such as, 2vs.1 and 3vs.1 typically reveal which team is dominating the match, particularly when those structures occur on the attacking side of that team's field. Thus, designing training exercises that create an overload for the attacking team may allow players to better adapt to such situations in a match. Finally, we found that as an attacking team moves closer to the goal, changes in player speed become more pronounced. It is therefore likely that encouraging such speed changes during training may facilitate the players' positioning inside finishing areas during a match.

Moreover, when players are connected with other players (in cooperation or competition) forming simplices, where the smaller simplices are also connected with other simplices, team coordination develops due to attunement to shared affordances and the creation of team synergies (Araújo and Davids, 2016). Training sessions may benefit from using the present analysis (e.g., most frequent cooperation/competition tag sets) and consequently design training activities that promote collective learning among groups of players (Travassos et al., 2016).

In the context of this article the criterion, closest player, for the formation of hyperedges was the only one used. The results presented at different levels of analysis are therefore conditioned and limited by this criterion. At the same time all these results where possible with only this parsimonious criterion and without any other assumptions.

Other limitation of the study is that there is no data about ball positioning, nor about "ball flux" (e.g., passes between the players). This type of interactions between players could be included by extending the proposed method with additional layers. In such layers, ball flux could be represented either as a link between players' or simplices, or alternatively as an additional term in the relationship, *R*, of the simplices.

Multilevel hypernetworks is a promising framework for soccer performance analysis that reveals important features of cooperative and competitive interactions during attacking plays. By considering space and time in multilevel analyses involving interactions between two or more players, we can obtain a richer understanding of real-world complex systems.

AUTHOR CONTRIBUTIONS

JR, main contribution regarding theoretical approach, method and results production. RL, significant contribution regarding method, software computation, and results production. PM, significant contribution on results reading and discussion and the impact to practitioners. DA, significant contribution regarding performance analysis and the general impression.

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APPENDIX

Algorithm 1 Build the simplex hyperedge set, S, from the set of all nodes, V

Require: Every node in V has one and only one node that is closest to it, $d_{Euc}(u, v)$ is the euclidean geographical distance beteeen nodes u and v

procedure BuildHyperedgeSet(V)
    $S \leftarrow \emptyset$ ▷ S, set of hyperedges build so far
    $Q \leftarrow V$ ▷ Q, set of nodes not yet in a hyperedge
    while $Q \neq \emptyset$ **do**
        $u \leftarrow i : i \in Q$ ▷ Get a focal node, u, not yet in a hyperedge
        $v \leftarrow j : d_{Euc}(u, j) \leq \min_{k \in V \backslash u} d_{Euc}(u, k)$ ▷ Get node, v, closest to u
        for each $\sigma : \sigma \in S$ **do**
            if $v \in \sigma$ **then** ▷ If closest node, v, is already in a hyperedge, σ
                $\sigma \leftarrow \sigma \cup \{u\}$ ▷ Node u is added to hyperedge σ
                $Q \leftarrow Q \backslash u$ ▷ Node u is done with
        if $u \in Q$ **then** ▷ If node u was not added to a simplex
            $\sigma_{new} \leftarrow \{u, v\}$ ▷ Create hyperedge, σ_{new}, with nodes u and v
            $S \leftarrow S \cup \{\sigma_{new}\}$
            $Q \leftarrow Q \backslash u$ ▷ Node u is done with
            $Q \leftarrow Q \backslash v$ ▷ Node v is done with
    return S

FIGURE A1 | Pseudocode for building the simplex hyperedge set.

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ORIGINAL RESEARCH
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Effects of Intensive Crew Training on Individual and Collective Characteristics of Oar Movement in Rowing as a Coxless Pair

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This case study examined how two rowers adapted their rowing patterns following crew training as a newly formed coxless pair. The two participants were expert (double-oar) single scull-boat rowers. Performing as a crew in the coxless-pair's sweep-boat, where each rower operates a single oar, on-the-water data were collected before and after a 6-week intensive team-training program. Rowing patterns were characterized by the horizontal oar angle, oar angular velocity and linear oar-water velocity profiles during the catch (minimal oar angle) to finish (maximal oar angle) half-cycles of the propulsive water phase. After crew training, rowers demonstrated a tighter synchronization and a closer correspondence in oar angle at the moment of catch, together with a closer matching of the evolution over time of their subsequent oar movements. Most likely due to the inherent asymmetries involved in sweep-boat rowing, the stroke rower also developed a somewhat longer-duration larger-amplitude oar movement than the bow rower. Remarkably, both rowers revealed changes in the inter-cycle variability of their individual patterns of rowing. While the initially more variable stroke rower improved the consistency of his rowing pattern over practice, the initially highly consistent bow rower on the contrary relaxed his tendency to always perform in the same way. We discuss how the crew performance changed over training and to what extent it was associated with changes in individual behaviors. Along the way we demonstrate that the often-used measure of average continuous relative phase does not adequately capture the particularities of the coordination pattern observed. Overall, the results obtained at the individual level of analysis suggest that team benefits were obtained through distinct adaptations of the rowers' individual rowing patterns.

Keywords: joint action, rowing, synchrony, crew behavior, individual pattern

INTRODUCTION

Joint action is considered as a form of social interaction whereby individual agents coordinate their movement in space and time so as to reach a common goal (Sebanz et al., 2006). While a considerable amount of research has focused on the nature and stability characteristics of coordinative states resulting from informational coupling between individual agents (see Schmidt and Richardson, 2008, for an overview), the tasks considered generally did not have a specific supra-coordinative goal. On the other hand, in tasks like dyadic manual precision aiming, where one participant controls the position of a pointer and another participant controls the position of a target (in the discrete task version, Romero et al., 2015) or a set of two targets (in the reciprocal task version, Mottet et al., 2001), the supra-coordinative goal to have the pointer coincide with the target(s) naturally structures the required between-participant coordination. Focusing on variance in the upper-limb joint angles, Romero et al. (2015) indeed demonstrated that inter-personal synergies were stronger than intra-personal synergies, while Mottet et al. (2001) demonstrated between-participant compensatory variability at the level of the two end-effectors (i.e., the control of the positions of the pointer and target-set).

More generally, in joint action tasks the individual agents' movements are shaped both by the current needs of their collective behavior and by the singular task demands that each individual agent faces. In this light, expertise in collective behavior tasks has been considered as the capability of individual agents to identify and achieve a specific contribution (e.g., Duarte et al., 2012; Benerink et al., 2016), thus reflecting a coordination of labor within the social joint-action system. Embedded in a process of compensatory variability between individual agents, the collective behavioral states may be expected to depend on the individual agents' abilities to adapt their own intrinsic behavioral dynamics to the needs of the cooperative effort. In order to characterize such adaptations at the level of the individual agents, in the present study we examined how a pair of rowers adapted their contribution to the joint action task of moving the boat forward after having followed an intensive crew-training (CT) program. By selecting a newly formed crew pair of expert rowers, the present study moreover provided an optimal framework for addressing task-goal driven adaptations in individual behavior in a real-life joint-action task.

In competitive crew rowing the individual rowers need to coordinate their actions in order to move the boat forward as fast and as efficiently as possible. Perfect synchronization of propulsive oar movement has often been cited as being a prime requirement for efficient rowing (e.g., Wing and Woodburn, 1995; Baudouin and Hawkins, 2004; de Brouwer et al., 2013; Cuijpers et al., 2015, 2016; Seifert et al., 2017). It is important to realize, however, that such a requirement cannot be indistinguishably applied to the two different types of boats used in competitive rowing. In sculling each rower simultaneously operates a pair of oars (one on the left and one on the right) and boats for (crew) sculling are therefore symmetrically rigged. In sweep-oar rowing, on the other hand, each rower operates a single oar (either on the left or on the right) and sweep-oar boats are therefore asymmetrically rigged. In sweep-oar rowing as a coxless pair, as studied in the present contribution, the crew consists of two rowers, with the bow rower being closest to the bow and the stroke rower being closest to the stern (see **Figure 1** for further details). In such a setting, perfect synchronization of oar movement, with its associated symmetrical power output, in fact results in yawing (resulting in changing direction) of the boat during each propulsive drive phase, thereby reducing overall efficiency (Hill, 2002; Barrow, 2010). Well-trained crews may thus be expected to have developed strategies to overcome this (Hill, 2002), while at the same time incorporating the inherently different roles resulting from the in-line placement (i.e., one behind the other) of the individual rowers (in both scull and sweep-oar boats). Indeed, as a result of such in-line placement, the stroke rower is not able to directly see his/her teammate(s). Because there is no cox (short for coxswain, an oar-less crew-member responsible for steering and race strategy), rowing as a coxless pair is self-paced. It is typically the stroke rower that is in charge of setting the rhythm, thereby potentially giving rise to leader-follower roles within the crew (Seifert et al., 2017).

In this light, we investigated how changes in the individual rowing behaviors of a coxless pair were observable over a large time span (i.e., across 6 weeks), after participants had been involved in repeated crew coordination practices. The investigation started from the very first step of their crew training. It ended after a one-month-and-an-half intensive team practice focused on enhancing their coordinative capability. The goal of the study was to simultaneously characterize the changes in the collective and individual rower behaviors.

MATERIALS AND METHODS

Participants and Procedure

Two 17-year-old men participated in the study. Having been admitted into the French National Rowing School (*Pôle Espoir Aviron – Nantes*), both were qualified as expert-level individual rowers. Each rower had more than 10 years of experience in single scull (two-oar) rowing. Rowers individually performed in the national competition and belonged to the French top 10. While both had rowed in crew boats during training sessions, neither had experienced dedicated crew training. Before engaging in the present study they had never rowed together in the same boat.

Data were collected during two on-water rowing sessions as a coxless pair (i.e., in an asymmetrically rigged sweep-oar boat where each rower operates one oar) that took place before and after a 6-week training program dedicated to crew rowing. We will refer to these two data-collection sessions as pre-CT and post-CT, respectively. The intensive CT program was managed by the national coach and comprised 26 (i.e., 4+ per week) on-water practice sessions, for a total of almost 50 h of coxless pair rowing practice. Each practice session typically consisted of two sets of 20–30 min of rowing separated by 5-min rest periods. During training sets, performed at frequencies of 17–28 strokes per minute (spm), rowers had to use maximal power during the drive (i.e., when the oar was in the water), so as to move the boat forward as fast as possible, and to recover when the oar was out of the water. During practice sessions, the coach followed the coxless pair in a motorboat, providing online feedback mainly focusing on the simultaneity of the oars' entry into the water, the orientation of the blades and the direction of the boat. Crew briefings providing further information were organized before and after each CT training session.

The pre-CT and post-CT data-collection sessions took place under calm water and stable weather conditions while rowing at

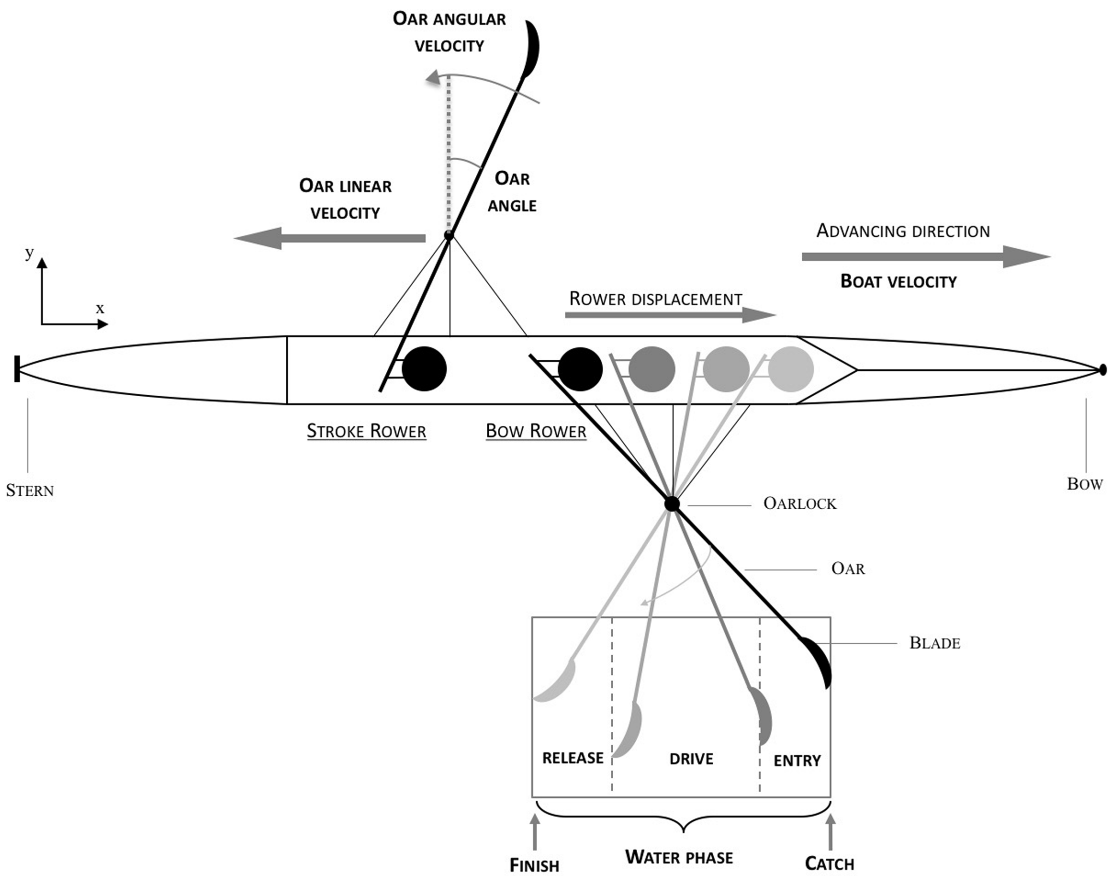

FIGURE 1 | Bird's-eye view of a coxless pair rowing situation. The water phase of oar movement is delineated by catch (minimal oar angle) and finish (maximal oar angle) points and consists of three parts, the entry, the drive, and the release.

constant pace of 17–18 spm under the same general instructions as described for the training sessions. Both rowers had extensive previous individual practice experience at this stroke rate. Moreover, it did not induce a level of fatigue that could be expected to alter the rowing patterns over the course of the approximately 20-min sessions during which data was collected.

The study was performed in accordance with the Declaration of Helsinki and the APA ethical guidelines. It was approved by an Institutional Review Board of the University of Nantes. The two rowers and their coaches were informed of the procedures. The rowers, their parents and the staff members in charge provided written informed consent. Both sessions analyzed in the present study were part of a larger research project (ANOPACy), also including qualitative phenomenological analyses of the experience of crew rowing, using individual rower verbalizations obtained during video-based self-confrontation interviews (R'Kiouak et al., 2016) and other rowers and rowing conditions (Seifert et al., 2017).

Data Collection and Analysis

During the pre-CT and post-CT sessions, behavioral data were collected at 50 Hz using the PowerLine system (Peach Innovations, Cambridge, United Kingdom). For the present purposes, we retained the time series of horizontal oar angles (delivered by position sensors in the oarlocks) and boat velocity (delivered by an impeller fixed under the shell). According to Coker (2010), the PowerLine angle sensors provide an accuracy of 0.5°. No accuracy data are available with respect to boat velocity measurements. For each session, the first 350 recorded strokes were retained for analysis.

Full time series of the 350 recorded strokes were first filtered using a low-pass Butterworth filter with a 7-Hz cut-off frequency, run through twice in order to negate the phase shift. Oar angular velocity (OAV) time series were subsequently derived using the first central difference method. The first 10 cycles were then removed in order to focus on stabilized performance, leaving 340 full strokes for analysis purposes. Samples of five subsequent strokes from the pre-CT and post-CT sessions are presented in **Figure 2**.

With overall crew performance quantified by boat velocity, data analysis focused on the collective level of between-rower coordination and the individual kinematic level of oar-movement patterns. At the individual rower level, different cycles of oar movement were identified by their catch and finish points, corresponding to the minimum and maximum oar angles (with zero defined as perpendicular to the boat, negative in the

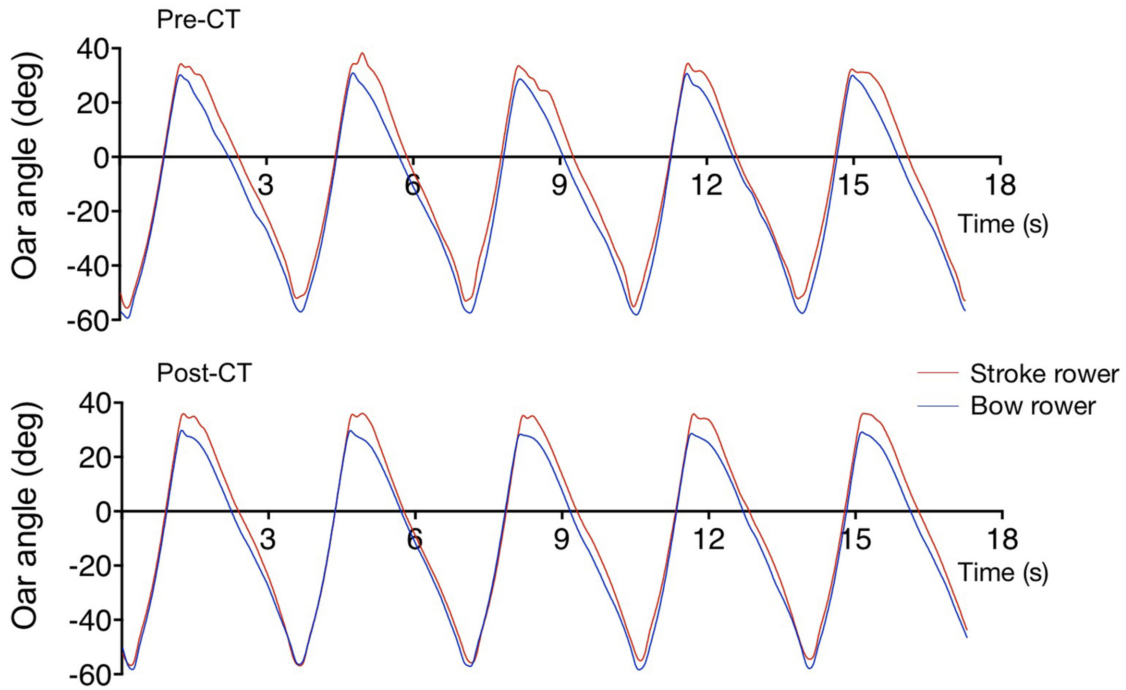

FIGURE 2 | Samples of oar movement of the stroke (red) and bow (blue) rowers for five subsequent strokes during the pre-CT **(Upper)** and post-CT **(Lower)** sessions.

direction of the bow and positive in the direction of the stern) for each rower separately. Starting from the catch point, a rower's full stroke is defined by four subsequent phases: *entry* (where the blade enters the water), *drive* (where the blade drives the boat forward), *release* (where the blade exits the water) ending at the finish point, and *recovery* from the finish to the next catch point (Coker, 2010, p. 45).

In order to quantify individual rower behavior, we extracted for each rower at each session the time series of oar angle and OAV of the half-cycles between catch and finish points. Each of these 340 half-cycles was time-normalized using steps of 2% half-cycle duration, resulting in 51 points per half-cycle. Average time-normalized half-cycles for each rower at each session were then obtained for oar angle and OAV by calculating the mean of all 340 corresponding values at each of the 51 points. The variability over half-cycles was calculated as the standard deviation over all 340 corresponding values at each of the 51 points.

As we were mainly interested in the (propulsive) drive phase, we identified this phase by determining when the oar moved faster than the water. To this end, for each of the 340 extracted half-cycles of each rower in each session, we determined the linear oar velocity in the direction of the boat's longitudinal axis by multiplying the tangential oar velocity (defined by the product of OAV and oar length) with the cosine of the oar angle. By calculating the difference between instantaneous linear oar velocity and instantaneous boat velocity and averaging over the 340 cycles, we obtained average time-normalized half-cycles of linear oar velocity with respect to the water [linear oar-water velocity (OWV)].

As can be seen from **Figure 3**, the drive phase (shaded areas under the curves where linear OWV is positive) ended closer to the finish point for the bow rower than for the stroke rower, at least during the pre-CT session. In order to compare the behavior of individual rowers on and between sessions, for both rowers we therefore selected the common (29-point) period from point 14 to point 42 (i.e., from 26 to 82% of the duration of the catch-finish half-cycle) for analyses of the drive phase.

For the analysis of individual rower behavior, oar angle kinematics were thus determined between the catch and finish points of each individual rower's actions (i.e., on separated time series). In examining the resultants plots (e.g., **Figure 3**) it is important to realize that these individual catch and finish points did not necessarily coincide in time, as becomes clear from inspection of **Figure 2**. In order to capture the collective behavior of the two rowers, we therefore extracted the 340 synchronous oar angle and OAV time series of the rowers during each (catch-to-finish) half-cycle of the stroke rower. After time-normalization to 51 points according to the procedure described above, for each of these 340 time-locked series we quantified between-rower coordination by the continuous relative phase (CRP) between the motions of the two oars during the catch-finish half-cycles. To this end, for each rower and each half-cycle, oar angle was normalized to a $[-1;+1]$ interval based on the minimal and maximal oar angles (i.e., amplitude normalized) and OAV was normalized by dividing OAV by peak OAV (resulting in a maximum of $+1$); Phase was determined as the angle (clockwise notation) formed by each point thus defined in the normalized phase plane. CRP was defined at each point as the difference

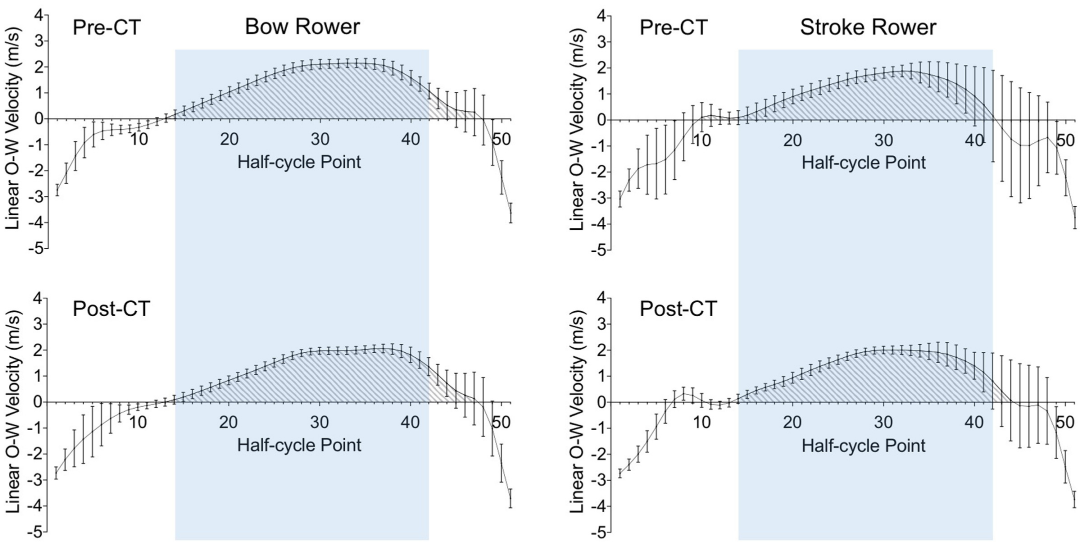

FIGURE 3 | Average time-normalized half-cycles for oar-water velocity from catch (point 1) to finish (point 51) for the bow (Left) and stroke (Right) rowers during the pre-CT (Upper) and post-CT (Lower) sessions. Error bars present the standard deviations over 340 half-cycles. The shaded area delineates the drive phase during which oar-water velocity is positive. The blue area indicates the common part of the drive phase (between points 14 and 42).

between the phases of the stroke and bow rowers (de Brouwer et al., 2013; de Poel et al., 2016; Seifert et al., 2017). A global measure of rower synchronization during the drive phase was obtained by calculating for each half-cycle the average CRP value over the period between points 14 and 42. This procedure thus resulted in 340 CRP values per session, with a measure of synchronization being provided by the mean and a measure of its variability being provided by the standard deviation over the 340 values. A complementary measure of space-time similarity of oar movement was obtained by calculating the root mean square (RMS) difference of the time-locked oar-angle time series of the two rowers during these same periods.

Statistical comparisons of means based on $n = 340$ observations were performed using independent-sample t-tests. Statistical comparisons of variability (defined as standard deviations over 340 observations) were performed using t-tests over the 29 points defining the drive phase. Paired tests were used for within-rower comparisons (pre-CT vs. post-CT for bow and for stroke) while independent sample tests were used for between-rower comparisons (bow vs. stroke at pre-CT and at post-CT). Because only one pair of rowers was considered in the present study, significant ($\alpha = 0.05$) effects were only considered when effect size (Cohen's d) reached at least the 0.50 threshold for a medium size effect (Cohen, 1988). Since, given the number of observations, any effect with effect size $d \geq 0.5$ was also statistically significant, we only reported d-values so as to stress substantive rather than statistical significance.

RESULTS

During the pre-CT and post-CT sessions rowers demonstrated stroke frequencies of 17.94 ± 0.46 and 17.37 ± 0.28 spm, respectively. The slightly (3.3%) lower stroke rate during the post-CT session was accompanied by a 2.2% lower average boat velocity (pre-CT 3.40 ± 0.08 m/s, post-CT 3.33 ± 0.09 m/s).

As can be already be seen in **Figure 2**, durations of catch-to-finish half-cycles were shorter than durations of the complementary finish-to-catch (recovery) half-cycles. During the pre-CT session the durations of the catch-to-finish half-cycles were 1.016 ± 0.046 s and 1.152 ± 0.111 s for the bow and stroke rower, respectively; during the post-CT session the corresponding durations were 1.057 ± 0.053 s and 1.118 ± 0.073 s, respectively. The difference in (catch-to-finish) half-cycle durations thus decreased over practice (from 0.137 to 0.061 s), but remained significant at the time of the post-CT session, $d = 0.69$.

While amplitudes of oar displacement from catch to finish were almost identical during the pre-CT session (bow 88.3 ± 1.6°; stroke 88.8 ± 1.8°), a difference came to the fore during the post-CT session, mainly due to an increase in amplitude for the stroke rower (bow 87.3 ± 1.3°, stroke 92.9 ± 1.3°; $d = 3.46$. During the pre-CT session peak angular velocity was slightly lower for the stroke rower (115.1 ± 3.3 deg/s) than for the bow rower (117.9 ± 3.3 deg/s), $d = 0.81$. This difference no longer existed during the post-CT session (bow 117.2 ± 3.1 deg/s; stroke 117.2 ± 3.6 deg/s; $d = 0.01$).

As can be seen from **Figure 4** (error bars), during the pre-CT session the bow rower demonstrated a particularly consistent pattern of oar angular (OA) displacement during the drive phase, with an OA variability (defined as the 29-point average of standard deviations over the 340 drives) of 1.80 ± 0.31°. The stroke rower's movements during this pre-CT session were considerably more variable ($d = 3.81$), with an OA variability of 6.15 ± 1.59°. Interestingly, over practice

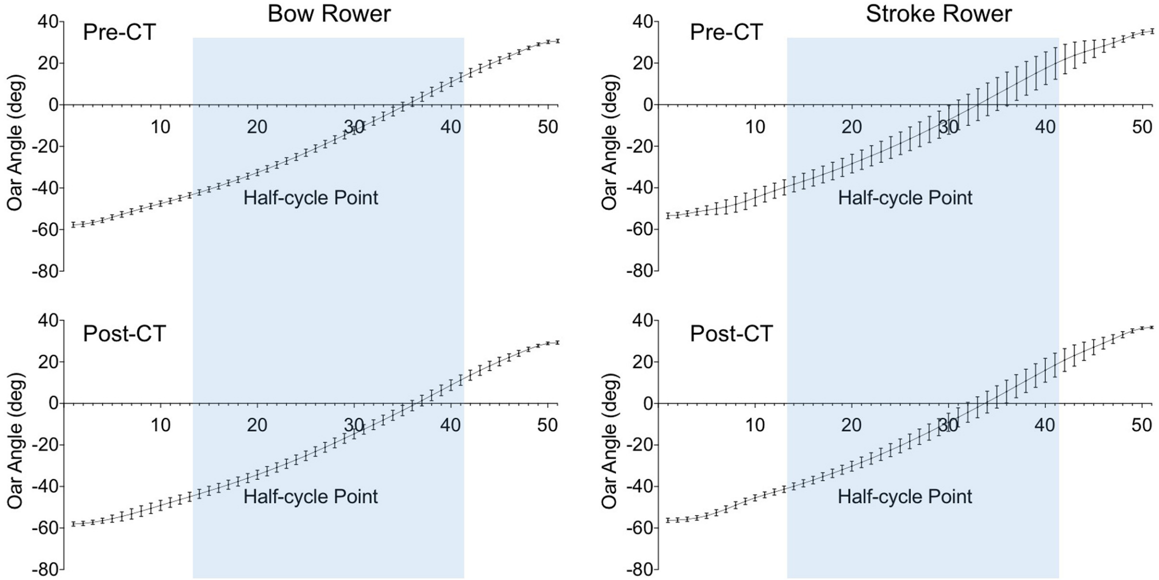

FIGURE 4 | Average time-normalized half-cycles for oar angle from catch (point 1) to finish (point 51) for the bow (Left) and stroke (Right) rowers during the pre-CT (Upper) and post-CT (Lower) sessions. Error bars present the standard deviations over 340 half-cycles. The blue area indicates the common part of the drive phase (between points 14 and 42).

not only the stroke rower's OA variability decreased (post-CT 3.88 ± 1.45°, d = 8.31), but the bow rower's OA variability increased (post-CT 2.34 ± 0.13°, d = 2.94). While the difference between individual rower OA variabilities thus decreased over practice, it remained significantly lower for the bow rower, d = 1.49.

A slightly different pattern of results emerged for the variability in OAV (**Figure 5**) during the drive phase. During the pre-CT session, the OAV variability was smaller for the bow rower (4.75 ± 0.40°) than for the stroke rower (9.03 ± 7.81°), d = 0.77. Both rowers decreased their OAV variability over practice, reaching 4.01 ± 0.59° for the bow rower (d = 1.35) and 5.68 ± 3.75° for the stroke rower (d = 0.73) during the post-CT session. Although the difference between individual OAV variabilities decreased over practice, it remained significantly lower for the bow rower, d = 0.62.

Applying the same analysis to the linear OWV (**Figure 3**) revealed a smaller OWV variability for the bow rower (0.21 ± 0.04 m/s) than for the stroke rower (0.47 ± 0.39 m/s) during the pre-CT session, d = 0.93. Both rowers decreased their OWV variability over practice, reaching 0.18 ± 0.05 m/s for the bow rower (d = 0.95) and 0.28 ± 0.21 m/s for the stroke rower (d = 0.99) during the post-CT session. Although the difference between individual OAV variabilities decreased over practice, it remained significantly lower for the bow rower, d = 0.63.

At the collective level, the RMS difference between oar positions (**Figure 6**) decreased from the pre-CT session (4.95 ± 2.38°) to the post-CT session (2.23 ± 1.77°), d = 1.30, indicating an increase in space-time similarity of the oar movements of the two rowers. Perhaps surprisingly, the nature of the between-rower coordination appeared to change as average CRP (**Figure 7**) evolved from −0.30 ± 4.44° (pre-CT) to −4.09 ± 3.86° (post-CT), d = 0.91, suggesting the coming to the fore of a phase lag of the stroke with respect to the bow rower. Inspection of **Figure 2**, however, suggests that, contrary to what is generally assumed (de Brouwer et al., 2013; de Poel et al., 2016; R'Kiouak et al., 2016; Seifert et al., 2017), average CRP may not adequately capture the subtleties of the changes in between-rower coordination. The timing of the catch by both rowers, for instance, became more closely time-locked, with the stroke-bow difference changing from −0.072 ± 0.055 s pre-CT to 0.003 ± 0.039 s post-CT (d = 1.57). Such a change was not observed for the timing of the finish, with the stroke-bow difference being 0.065 ± 0.105 pre-CT and 0.064 ± 0.081 post-CT, d = 0.01. Thus, during the pre-CT session, the bow rower entered the water somewhat before the stroke rower and left the water somewhat after the stroke rower. Over practice this timing difference disappeared for the catch, with both rowers entering the water at the same time after training, but not for the finish (release). The timing of the catch was not the only aspect that changed over practice; the position of the oars (i.e., oar angles) at catch and finish also evolved. The stroke-bow difference in oar angle decreased for the catch, from 4.18 ± 1.67° pre-CT to 1.79 ± 1.39° post-CT (d = 1.56), while the stroke-bow difference in oar angle increased for the finish, from 4.67 ± 1.36° pre-CT to 7.34 ± 0.90° post CT (d = 2.32). As can be seen from **Figure 2**, these results indicated that over practice the two rowers came to adopt similar oar angles when entering the water, while accentuating their difference (with a larger maximal angle for the stroke rower) when leaving the water.

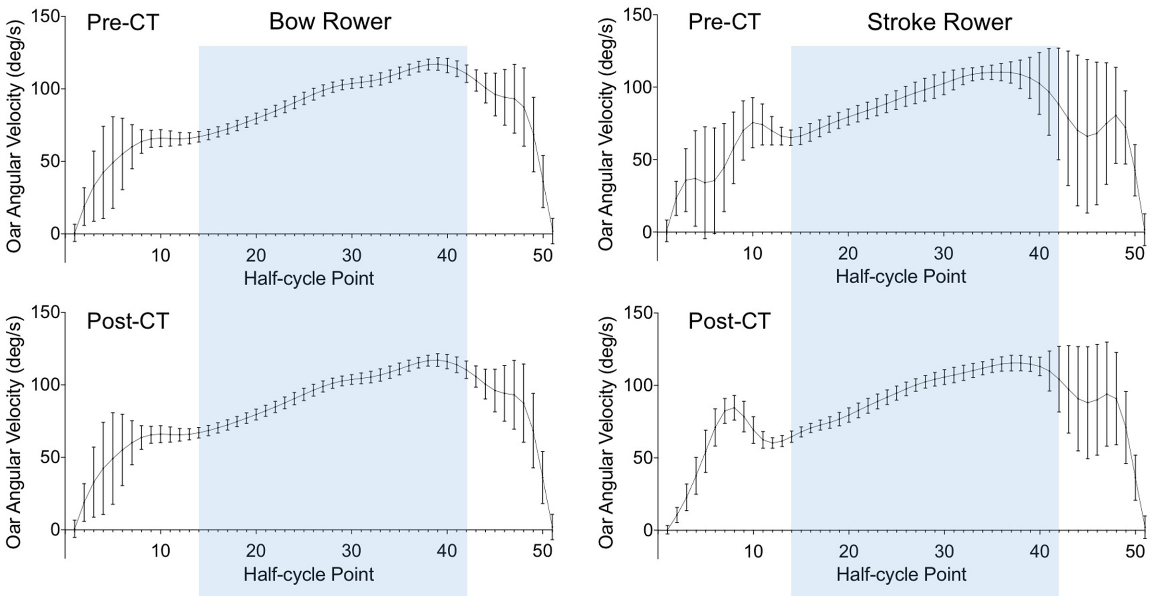

FIGURE 5 | Average time-normalized half-cycles for oar angular velocity from catch (point 1) to finish (point 51) for the bow (Left) and stroke (Right) rowers during the pre-CT (Upper) and post-CT (Lower) sessions. Error bars present the standard deviations over 340 half-cycles. The blue area indicates the common part of the drive phase (between points 14 and 42).

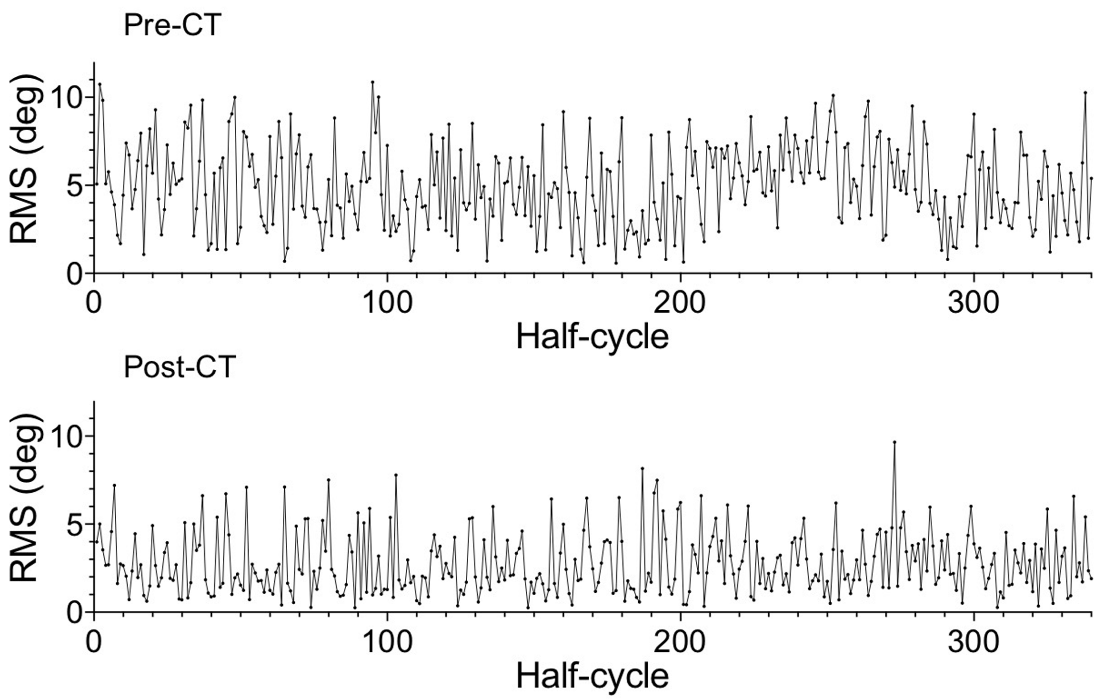

FIGURE 6 | Root mean square (RMS) of the difference between oar angles of the stroke and bow rowers for the 340 catch-finish half-cycles of the pre-CT (Upper) and the post-CT (Lower) sessions.

Overall, changes at the collective level may thus be characterized as follows. Compared to the pre-CT session, during the post-CT session the rowers demonstrated a tighter synchronization and a closer correspondence in oar angle at the moment of catch. They also more closely matched the evolution over time of their subsequent oar movements, as indicated by

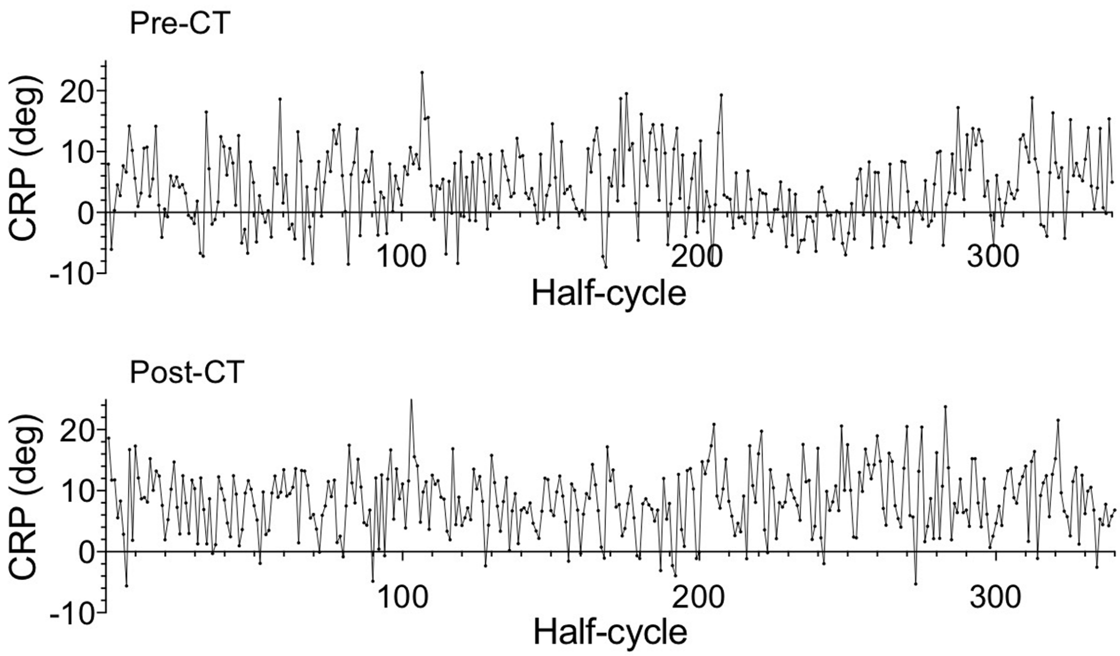

FIGURE 7 | Average continuous relative phase (CRP) of the rowers' oar movements for the 340 drive phases of the catch-finish half-cycles of the pre-CT (Upper) and the post-CT (Lower) sessions.

the RMS oar-angle difference results. Ending the movement later than the bow rower, the stroke rower continued his oar movement up to a larger amplitude. The apparent lag of the stroke rower, as indicated by the average CRP results, is in fact the result of this pattern of coordination.

DISCUSSION

The purpose of the present study was to characterize how extensive training practice on a real-life performance-oriented joint-action task affected behavior at the collective and individual-agent levels. To this end we examined how the collective and individual oar behaviors of a newly formed pair of rowers evolved in sweep-oar rowing as a coxless pair over a one-and-a-half-month intensive crew training program. With both participating rowers being recognized individual sculling experts, the study allowed to focus on behavioral changes related to adaptation to the new task, without such changes being superseded by learning effects at the level of individual oar-handling capabilities.

At the scale of the collective crew behavior, results first of all indicated an overall increase in the space-time similarity of individual rowing patterns, as revealed by the decrease in RMS oar angle differences. This was to a large extent due to the catch points (marking the onset of the blades' entry into the water) becoming more tightly matched between the two rowers in terms of both timing and oar-angle magnitude. However, the results also suggested a subtler change in the nature of the coordination of the rowers' oar movements, with the stroke rower, developing an oar movement of a longer duration, continuing up to a larger amplitude than the bow rower in the post-CT session. This finding might be interpreted as the crew's solution to (partially) avoid channeling the boat into yawing during the drive phase: full space-time similarity of the rowers' oar movements in the asymmetrically rigged sweep-boat would indeed result in differences in the moments produced by each rower (Barrow, 2010). We note that —at least for sweep-boat rowing— the above-described particularities of the observed coordination pattern render the often-used average CRP measure (e.g., de Brouwer et al., 2013; de Poel et al., 2016; R'Kiouak et al., 2016; Seifert et al., 2017) rather ill-fitted to the job of comprehensively (and comprehensibility) capturing a rowing crew's coordination pattern. This remains true, even when adopting a calculation method suitable for analysis of the water phase (catch-to-finish) half-cycles, as detailed in the Section "Materials and Methods" of this contribution. While at the moment of catch Relative Phase (RP) in the post-CT session was on average in fact very close to 0° (since the average catch time difference was a mere 0.003 s), the between-rower differences in duration and amplitude of oar movement resulted in average CRP values of −0.3° and −4.1° for the drive phases of pre-CT and post-CT sessions, respectively. Interpreting the latter as indicating that, overall, during the post-CT session the stroke lagged the bow rower (or, alternatively, that the bow led the stroke rower) would clearly not do justice to the subtleties of the coordination pattern observed. From the observation that during the post-CT session RP ≈ 0 at the moment of catch, we conclude that the crew studied did not appear develop a leader-follower relation (cf. Seifert et al., 2017). As illustrated in **Figure 2**, the two rowers rather performed in almost perfect harmony until the very end of the drive, with the stroke rower continuing his oar movement for a short time after the bow rower's had ended.

The foregoing discussion already brings out that results observed at the level of the individual rowers consolidated and enlightened the idea that improvement in crew behavior was rooted in changes in how each rower performed his own movement. Interestingly, apart from the results on oar movement amplitude and timing alluded to above, we also observed training effects at the level of the *variability* of the kinematic patterns of oar movement (oar angle, OAV, and linear OWV). On the post-CT session the stroke rower demonstrated increased consistency (i.e., lower inter-cycle variability) over the drive phase on all three measures. While the bow rower also improved his consistency for OAV and linear OWV, he revealed an increase in variability in oar angle displacement during the drive phase.

The finding that, at the level of oar angular displacement, crew training resulted in a decrease of inter-cycle variability for one rower and an increase for the other rower is particularly noteworthy, as it speaks to the adaptability of individual patterns. Following training, the (initially more variable) stroke rower performed in a more stable manner, while the bow rower relaxed his initial tendency to always perform in the same way. Interestingly, this result highlights how a team member can change his behavior in terms of reducing its absolute efficiency (i.e., self-deteriorating his rowing pattern by increasing its variability) in order to obtain benefits at the team scale. Although we do not have direct proof for this, we suggest that the bow rower became better coupled to the stroke rower, enhancing the process of reciprocal compensation (Mottet et al., 2001; Araújo and Davids, 2016) that supports adaptability in joint action.

Overall, the results of the present case study, addressing both the crew- and individual-levels of analysis, allow us to tentatively discuss what building a team might imply in terms of the adaptations required. Both rowers were able to change their own individual patterns when they were trained to row as a team. Our study suggests that rowing together not only called for finding an efficient timing relation (i.e., finding the *when* of each rower's oar movement), but also required each rower to change the *how* of the rowing movement. The training effects observed here complement findings from other domains (such as industrial and organizational psychology, see for instance Gorman et al., 2010) indicating that team building relies, at least in part, on *interactions*. Moreover, introducing perturbations into established team functioning (e.g., by changing teammates, Gorman et al., 2006) was found to improve team adaptability to novel situations. Procedures for improving team performance may thus benefit from taking a process-oriented, interaction-based approach (Gorman et al., 2006) rather than limiting oneself to a shared knowledge-oriented approach (Cooke et al., 2000). Indeed, the changes observed in (the variability of) rowing behaviors in the present study suggest that improved team performance was grounded in changes in the intrinsic dynamics of the individual team members. One might even speculate that the coaches' choice to place the initially hyper-consistent rower in the bow (rather than in the stroke) position, thereby ensuring that he continuously saw his partner, originated from the perceived need to make him more adaptive in order to be successful in crew rowing.

Such adaptation of each individual's intrinsic dynamics over crew practice brings up the question to which extent individuals having rowed in a team would be able to rapidly recover their individual patterns of rowing when performing alone anew (i.e., in their individual sculling practice). Oullier et al. (2008) reported that, after having been influenced by a sustained interaction, individual agents did not immediately return to their own intrinsic movement pattern, a phenomenon they referred to as social memory. Recently, Masumoto and Inui (2017) reported that in a joint motor action practicing together was important to enhance interaction capabilities of individual participants, and that retention effects were observable not only from individual practice to team performance, but also from team practice to individual performance. The question whether such effects may also exist in sport-specific practices opens promising directions for future research.

CONCLUSION

We described how crew rowing changed over training and the extent to which it was associated with related changes in individual behaviors. Among the key results, our case study suggested the capability to change individual patterns of rowing as being the key element underlying the positive collective behavioral transformation. Our results also proposed individual variability of behavior as being an important variable to consider, while the need to either decrease or increase it to obtain team benefits may be task-dependent. In terms of the questions that remain open, the extent to which individual signatures converge or diverge through team training (and how it depends on initial (dis)similarities) should be further investigated in future research.

AUTHOR CONTRIBUTIONS

MF, MR, and JB conceived, designed and ran the study. MF, MR, RB, and JB analyzed and interpreted the data. All authors participated drafting the work and/or revising it critically for important intellectual content. The final version submitted was approved by all authors.

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Are Neurodynamic Organizations A Fundamental Property of Teamwork?

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When performing a task it is important for teams to optimize their strategies and actions to maximize value and avoid the cost of surprise. The decisions teams make sometimes have unintended consequences and they must then reorganize their thinking, roles and/or configuration into corrective structures more appropriate for the situation. In this study we ask: What are the neurodynamic properties of these reorganizations and how do they relate to the moment-by-moment, and longer, performance-outcomes of teams?. We describe an information-organization approach for detecting and quantitating the fluctuating neurodynamic organizations in teams. Neurodynamic organization is the propensity of team members to enter into prolonged (minutes) metastable neurodynamic relationships as they encounter and resolve disturbances to their normal rhythms. Team neurodynamic organizations were detected and modeled by transforming the physical units of each team member's EEG power levels into Shannon entropy-derived information units about the team's organization and synchronization. Entropy is a measure of the variability or uncertainty of information in a data stream. This physical unit to information unit transformation bridges micro level social coordination events with macro level expert observations of team behavior allowing multimodal comparisons across the neural, cognitive and behavioral time scales of teamwork. The measures included the entropy of each team member's data stream, the overall team entropy and the mutual information between dyad pairs of the team. Mutual information can be thought of as periods related to team member synchrony. Comparisons between individual entropy and mutual information levels for the dyad combinations of three-person teams provided quantitative estimates of the proportion of a person's neurodynamic organizations that represented periods of synchrony with other team members, which in aggregate provided measures of the overall degree of neurodynamic interactions of the team. We propose that increased neurodynamic organization occurs when a team's operating rhythm can no longer support the complexity of the task and the team needs to expend energy to re-organize into structures that better minimize the "surprise" in the environment. Consistent with this hypothesis, the frequency and magnitude of neurodynamic organizations were less in experienced military and healthcare teams than they were in more junior teams. Similar dynamical properties of neurodynamic organization were observed in models of the EEG data streams of military, healthcare and high school science teams suggesting that

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neurodynamic organization may be a common property of teamwork. The innovation of this study is the potential it raises for developing globally applicable quantitative models of team dynamics that will allow comparisons to be made across teams, tasks and training protocols.

Keywords: teamwork, EEG, social coordination, team neurodynamics, information theory, entropy, uncertainty

INTRODUCTION

We all exist in continual perception/action cycles where we sample the environment, actively compare our perceptions with our probabilistic representations of the incoming information, adjust our models accordingly and then resample and/or change the environment. The goal of these cycles is to optimize the values and costs of future actions in order to minimize surprise. At the intersection of value and costs is the uncertainty that becomes resolved by this process.

Much of this decision-making activity is orchestrated by implicit brain process and occurs rapidly (Hsu et al., 2005); it has been proposed that human mental processes have evolved to minimize perception-model errors across systems and avoid the costs of surprise (Barlow, 1961; Friston, 2010).

These ideas have been encapsulated by Friston (2010) into a model, the free energy principle that develops a unified account of perception, action and learning (**Figure 1**). The free energy principle proposes that of the large number of physiological and sensory states that exist, there is a high probability that an individual's current state exists within a much smaller state space roughly defined by homeostatic requirements; i.e., the system is optimized and predictable for the most part. Occasionally however, large prediction errors arise between incoming information and internal probabilistic representations and these errors trigger parts of these systems to drift from homeostatic boundaries and the system becomes less predictable as a result of this surprise. From information theory, this change in predictability can be described as an increase in the uncertainty, or entropy of the system (abbreviated *H* in this paper).

Entropy is the average surprise of outcomes sampled from a probability distribution or density. A density with low entropy means that, on average, the outcome is relatively predictable, while a system with higher entropy would be less predictable. Entropy is therefore a measure of uncertainty.

When entropy gets too high new cognitive organizations are thought to emerge (Zipf, 1949), and through general error correcting and learning processes the system returns to within the homeostatic bounds. It is these reorganizations that we are interested in, primarily at the neurodynamic level of teams.

It is not difficult to extrapolate the free-energy principle to teams as surprises also happen during teamwork, especially with teams performing complex tasks where no two task instances are the same. In teams however, each person must now consider their actions, not only with regard to their roles in a changing environment, but also with regard to those other persons, each of whom is a complex system with a slightly different dynamic perspective of the environment. Nevertheless, the overall idea of minimizing the prediction error between incoming information (from the task and other team members) and an individual team members' representation of the situation is analogous to minimizing surprise.

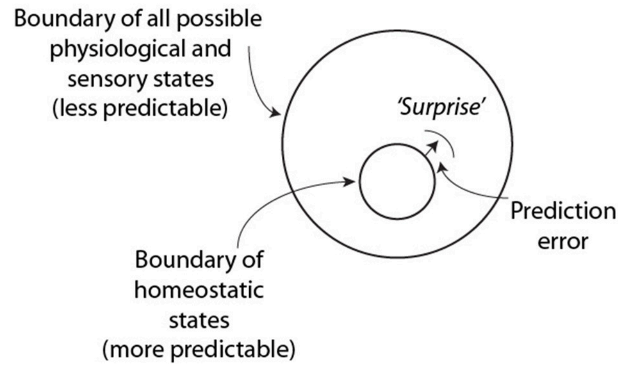


FIGURE 1 | Tenants of the free energy principle and the predictability of surprise (based on Friston, 2010). This figure shows a part of the homeostatic boundary that became shifted by a surprising event in the environment.

As resolving the cross-person (i.e., cross-brain) uncertainty will occur external to individual brains (through speech or gestures for instance), the mechanisms for optimizing the prediction error in teams are likely to be more complex and lengthy than those postulated to exist in individuals. Occasionally, due to these complexities and temporal delays, a team's decisions will be suboptimal and the team must dynamically reorganize into a configuration that is more appropriate for the immediate situation or alternatively, change the situation. This requires not only a re-assessment of the present situation, but also the mental "playing forward" of alternative approaches, with the eventual selection of an action by the team with potentially the best outcome (Schacter et al., 2007).

In this study we ask: What are the neurodynamic properties of these reorganizations in teams, how are they induced, and how do the dynamics differ among the team members? We take an information-organization approach in answering these questions in this paper as we believe this may provide a general and extensible quantitative framework for investigating teamwork across different teams performing different tasks.

The paper begins with an illustration of the overall modeling approach using the hypothetical dynamics of a theoretically perfect team where we speculate on how these dynamics might change when team members get "out of synch." This section is followed by more detailed descriptions of the modeling approach for exploring the neurodynamical and informational relationships between the organizations of individuals and teams.

The third section provides empirical evidence for the variety and importance of different neurodynamic organizations during teamwork. These sections draw from studies we have performed with high school teams performing map navigation tasks (Stevens and Galloway, 2014), submarine teams performing required navigation training exercises (Stevens et al., 2011, 2013; Stevens and Galloway, 2015) and healthcare teams (Stevens et al., 2016a). The similar dynamical and observational principles arising from these different tasks suggest that the phenomena being studied might be a fundamental property of teamwork.

MATERIALS AND METHODS

Neurodynamics of A "Theoretically" Perfect Team

The goal of the first section is to describe how the constraints of inter-personal communication and joint resolution of uncertainty might contribute to the changing neurodynamics of teams performing complex tasks. This example focuses on a three-person team although previous data from submarine navigation teams suggests the approach can be scaled to 5–6 person teams with certain simplifying assumptions that will be discussed in subsequent sections.

A starting assumption behind this example is that the efficiency and effectiveness of a team performing a complex task is enhanced by the fast and precise sharing of information, regardless of the interoceptive or exteroceptive uncertainty or noise in the system. We begin by postulating that each of the three team members has three possible energy levels, below average, average and above average, which represent the EEG signal power (in micro-volts) in a frequency bin recorded from scalp sensors; these levels can change every second. These three states could easily be quarters or fifths, or other discrete bins, with the associated scale-up costs in model computation.

The one-second interval is a theoretically plausible number for teams as periods of functional brain connectivity associated with speech or playing guitar in duets (Stephens et al., 2010; Sanger et al., 2012), and non-verbal recognition (Hari, 2006) occur in the 250–500 ms time range, or a bit over a half a second for a two person action-response round trip; in reality individuals in teams probably speed this up by predicting ahead, although at a cost of increased uncertainty (Hsu et al., 2005).

The analysis we describe is simplified as only one EEG frequency bin is being modeled that is within the range of human cognition, and easily available for research "in the wild." This dimension generally spans the 0.1 to 100 Hz frequency range as below this range other physiologic signals generated by respiration, heartbeats, electrode pops etc. may confuse the patterns and above this, electromyographic signals become a serious confounder. We also assume that the data was recorded from a single sensor site on the scalp. As described in the next section we currently model 1 Hz frequency bins from the 1- 40 Hz EEG frequency range that is simultaneously obtained from up to 19 sensor sites; i.e., the examples described below are generally repeated 760 (i.e., 40×19) times for each person in an experiment (or 2,280 times total for a 3-person team).

Next, a way of representing the state of each individual as a part of a team at any moment of the performance is needed; i.e., the state of each team member in relation to the other team members as well as to the immediate context of the task (**Box 1**). These combinations are represented as symbols with histograms showing the power level combinations for the team; with three energy states per person, and three persons, 27 unique symbols are needed. These symbols are termed Neurodynamic Symbols (*NS*), and the 27 symbols form a collection of states that together describe the expression of *NS* for a performance; this collection is termed a Neurodynamic State Space (*NSS*) and is shown in **Figure 2A** for a three-person team and **Figure 2B** for a dyad. A data stream of these symbols contains a neurodynamic history of the team performance, much like the codons in DNA.

The *NSS* contain topological structures that enhance the interpretation and visualization of team neurodynamics. The symbols toward the beginning of the *NSS* in **Figure 2A** (i.e., 1–4) represent periods where most of the team members had low EEG power levels, while those *NS* toward the end (24–27) represent times where most team members had high EEG power. Also, moving down each column in the *NSS* shows that only one person of the team is changed, going from low to average to high power. This *NSS* serves as a lookup table when visualizing the neurodynamics of teams.

Now imagine a fully connected, tightly coupled (in a network sense) experienced team so familiar with their goals, individual tasks, and team roles that they can engage in "mental time travel" (Schacter et al., 2007) and predict the future such that the future

BOX 1 | GLOSSARY OF TERMS.

- *Neurodynamic Symbols* (*NS*) are symbolic representations of the momentary EEG power levels of a neurodynamic marker for each team member.
- *Neurodynamic Symbol States (NSS)* are a collection of *NS* that together describe a team's performance.
- *Neurodynamic Data Streams (NDS)* are the second-by-second concatenated sequences of *NS* that temporally span a task performed by the team.
- *Neurodynamic Entropy* (NS_H), also called team entropy, is a quantitative measure of the distributions of *NS* in a *NDS* when examined over a moving window of time, often 60 s or 100 s. The quantitative information unit is called a bit, where **one** bit of information indicates that on average, the uncertainty of a process is reduced by a factor of **two** with **one** bit of information.
- *Neurodynamic Organization* (ND_Ω) is a quantitative estimate of organization reflecting periods of increased neurodynamic order. ND_Ω is calculated by subtracting the Shannon entropy of the *NDS* obtained over a 60 or 100s moving window, from the entropy of the *NS* stream after it has been randomized (i.e., $ND_\Omega = NS_{H\ random} - NS_H$). Neurodynamic organization can be calculated either from the entropy levels of individual team members or from the team entropy. When referring to individual's neurodynamic organization we will prefix it with the italicized word individual, i.e., *individual* ND_Ω.

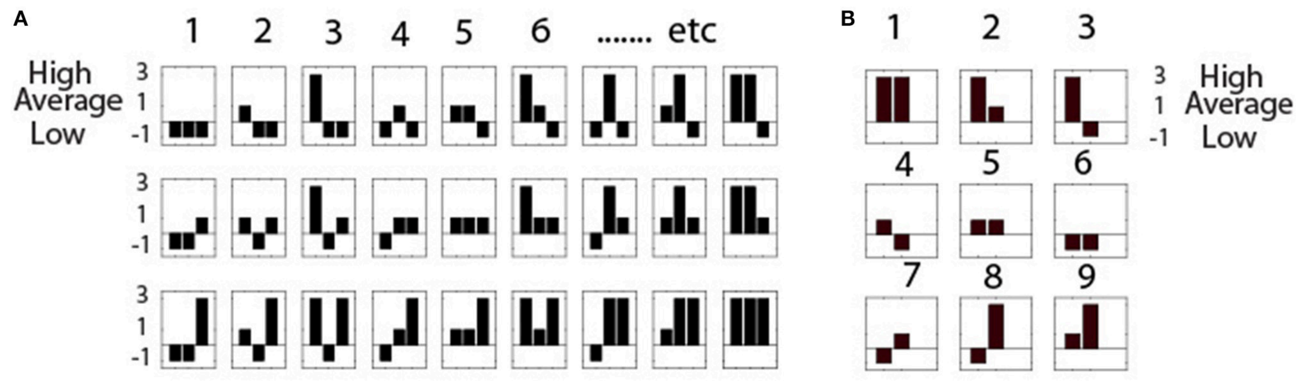


FIGURE 2 | Neurodynamic State Spaces. (A) Neurodynamic symbol state space for a three person team with high, medium or low EEG power levels. The legend on the left shows that low power is represented by -1, average by 1, and above average power levels by 3. As these values are treated symbolically they do not affect calculations, but do enhance visualization. Each of the three histograms in each *NS* represents a team member. **(B)** The nine symbol *NSS* for dyads.

holds few surprises. For such a team, each person's responses to changes in the task and the responses of other team members would be limited primarily by the latencies imposed by cognitive and motor systems (Suzuki et al., 2012).

This theoretically perfect team would also understand and trust their teammate's likely responses, so communication and strategizing delays would be those imposed by the mechanics of action understandings, speech processing and information exchange described earlier. To the extent that the task activities and team member interactions are sufficiently predictable to avoid surprises, the dynamical structure of this team might be highly variable as the members maximize the flows of team information content by flexibly using all of the states available in the 27 *NSS*.

This idea of maximizing variability to maximize information transmission might seem at odds with the more predictable smaller physiologic and sensory state space that was optimized for homeostatic processes in **Figure 1**. The difference is in the temporal scales over which processes are optimized. The constraints described in **Figure 1** have been optimized by evolution to make life possible. These processes continually transfer information from the environment to the genome to match the homeostatic boundaries with the selection pressures of the environment. In teams there is no similar genetic selection during a teams' lifetime, and the team's success depends more on maximizing the efficiency and effectiveness of the major task and teamwork processes, with the transfer of information among team members being paramount.

An example of the possible dynamics of this team is shown in **Figure 3A** where each of the 27 symbols in the *NS* data stream are sequentially plotted. Here the momentary changes at the neurodynamic level associated with the task work and teamwork would be couched within the 1 s sampling window so there are few repeating symbols due to slow social coordination and information sharing.

While the symbol distribution appeared random for this team, the entropy of this Neurodynamic Symbol Data Stream (abbreviated *NDS*) ($H = 4.64$ bits) showed that it was less than the theoretical maximum entropy for 27 symbols ($H = 4.76$ bits) indicating a non-random distribution of symbols, i.e., there is some hidden organization, perhaps due to system noise or the team's threshold tolerance for surprise. Nevertheless, the overall neurodynamic variability of the team was high suggesting efficiency as a discrete symbol set with high variability can convey more information than a symbol set with low variability. These ideas are consistent with the efficient coding hypothesis (Barlow, 1961) which states that the goal of the nervous system is to maximize information about the environment, and in doing so, to minimize the energy expended for each bit of information.

Now suppose one (or more) team members was less experienced than the others and became delayed by the unfolding events leading to increased surprise (in the free-energy principle sense) and deliberation by that person and the team (Kaufman et al., 2015). To resolve this new uncertainty the team members would need to become more predictable (i.e., less variable) to each other and this higher predictability could be accomplished by increased organization. In our theoretical situation this increased neurodynamic organization would be characterized by increased *NS* redundancy. Increased redundancy of information is common in nature as it is one way to ensure effective communication.

Figure 3B shows two periods of increased *NS* redundancy in the 1000 s performance. The first occurred between ~125 and 275 s and was characterized by the selective expression *NS* 18–27, which from **Figure 2** were periods where there was a tendency toward higher EEG power levels across the team members, and the second was between ~525 and 625 s where *NS* 1–10 were selectively expressed i.e., a tendency for lower EEG power across the team. During these periods the teams would be acquiring more information to reduce the individual and team's prediction errors, and bring their prediction model of the world closer the real model of the situation.

As described in the next section, the reduced variability of the symbols during these periods would result in lower entropy levels. Practically this might occur by changing the flow or content of information sharing across the

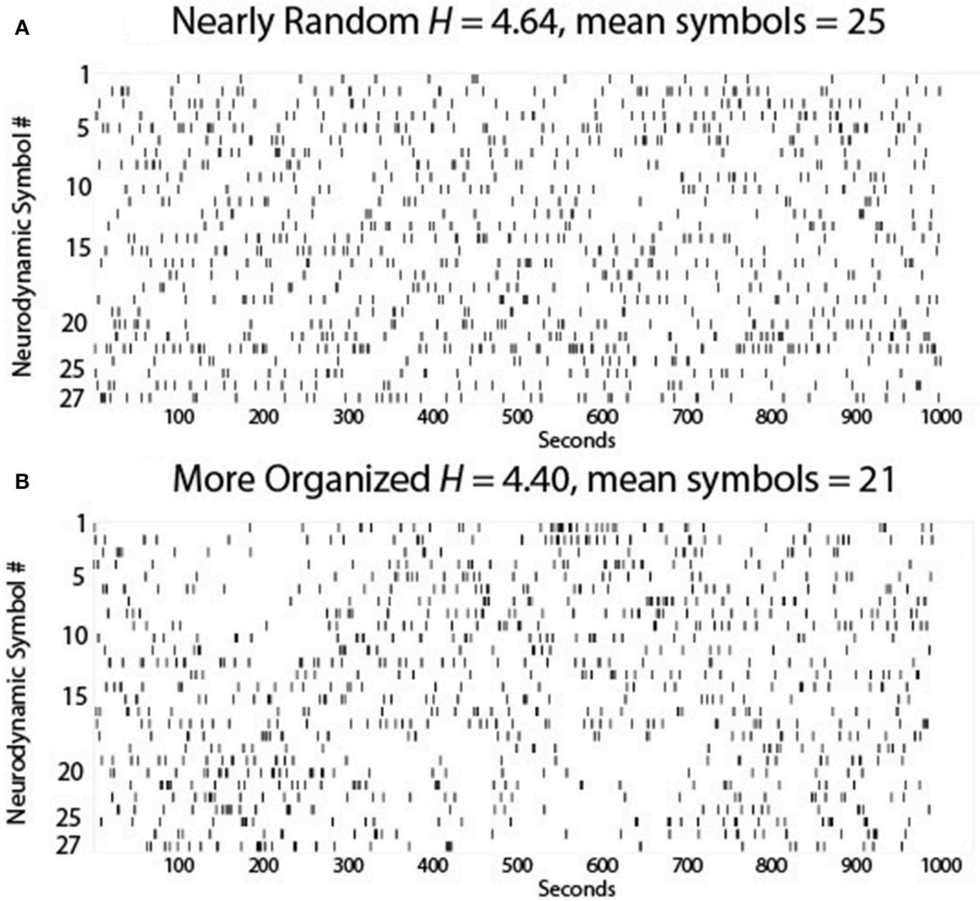


FIGURE 3 | The 27 *NS* of the *NSS* are plotted each second for (A) a theoretically near-perfect team, and **(B)** a team characterized by less *NS* variability. The symbol number is on the *Y*-axis and the time in seconds is on the *X* axis.

team (Kiekel et al., 2004), deliberately slowing down the pace of the task (Moulton et al., 2010), re-organizing the structure of the team, or re-organizing the structure of the task.

Depending on the coupling of the systems involved in teamwork (Hasson et al., 2011), these changing organizations would ripple over time until homeostasis for the team is re-established. Depending on the situation, the team would either return to pre-perturbation entropy levels or remain in a more organized state attentive to further surprise.

While acquiring more information to reduce uncertainty is beneficial for the team, what are the costs? Team re-organizations require energy. In information theory, reducing uncertainty is synonymous with acquiring more information, and acquiring more information requires energy. According to Szilard (1929), the act of acquiring information from a system generates entropy, or equivalently, it has an energetic cost due to the very nature of the procedure. He showed that the minimum amount of energy required to determine one bit of information is kT ln(2) Joules/bit, a quantity Landauer (1961) generalized to any way of manipulating or processing information such as measuring, encoding, displaying, a yes/no decision, etc. From the second law of thermodynamics, as the organization of a team increases (i.e., decreased entropy), it must increase entropy somewhere else, the most likely source being through energy production where complex molecules (sugar, ATP) or macromolecules (glycogen) are broken down, increasing the disorder. Such increased energetic costs associated with social coordination have been seen as increased BOLD signals in the medial prefrontal cortex of individuals simultaneously scanned during a deception team task (Montague et al., 2002).

The above discussion raises questions: Can we begin to populate models of teamwork with quantitative data that reflects the above ideas, and with what is understood to be expertise? Are team members in fact fully connected, and if so, how tightly linked are the couplings across different team members during different teamwork measures? Are there preferred couplings among team members depending on the task, or training protocol, or training site, and does this make a difference? How closely related are the models being revealed by neurodynamics, communication and behavioral measures? The next section describes the modeling approaches that might be used to approach these questions.

Tasks and Participants

Map Navigation Task

In the Map Task (MT) the team members faced each other while viewing a computer displaying a map with multiple landmarks (Doherty-Sneddon et al., 1997). The two maps were similar but not identical and students could not see each other's map. The instruction giver [Giver, abbreviated (G)], had a printed path through the landmarks and verbally guided the follower [Follower, abbreviated (F)] in duplicating that path. Students completed the Map Task using speech exchanges to determine where the paths should be drawn. The resulting speech was unscripted, fluent and contained easily identified goals (Stevens and Galloway, 2014).

Submarine Piloting and Navigation

Submarine Piloting and Navigation (SPAN) simulations were required exercises for Junior Officers in the Submarine Officer Advanced Candidacy course at the US Navy Submarine School. SPAN sessions contained three training segments: Briefing; Scenario; and Debriefing. Briefing was where the team reviewed the environmental conditions and other ships in the area, and statically established the submarine's position. The Scenario was the training part of the navigation simulation where events included: encounters with approaching ships, the need to avoid shoals, changing weather conditions, and instrument failure. The Debriefing was an after-action review where all team members participated in critical performance discussions (Stevens et al., 2012).

Healthcare Simulations

The simulations developed for healthcare also followed the standard training format beginning with a Briefing describing the goals of the exercise. This was followed by a short 5–10 min introduction including the simulated patient history which set the stage for the task simulation that lasted 15–20 min. A reflective Debriefing was then led by the instructor (15–20 min). The core construct of this simulation series was ventilation with procedural goals of demonstrating (1) the technical skills of supporting the airway of an obtunded patient, (2) the cognitive goals of carrying out team-based approaches to patients with decreased mental status; and, (3) practicing role assignment during care of a patient with an urgent/emergent clinical condition (Stevens et al., 2016b).

Ethics Statement

Informed consent protocols were approved by the Biomedical IRB, San Diego, CA, the OSF Healthcare Institutional Review Board, and the Naval Submarine Medical Research Laboratory Institutional Review Board, and written informed consent was signed by all participants to participate in the study and to have their images and speech made available for additional analysis. To maintain confidentially, each subject was assigned a unique number, known only to the investigators of the study and subject identities were not shared. This design complies with DHHS: protected human subject 45 CFR 46; FDA: informed consent 21 CFR 50. The selected examples presented in this paper were chosen from 15 Map Task, 16 Submarine Piloting and Navigation, and 6 healthcare team performances.

Electroencephalography

Prior to neurodynamically modeling the team the raw electroencephalographic (EEG) data from each team member were synchronized with each other through markers inserted into the data streams during data collection and then visually inspected for motion and other artifacts. Bad sensor channels or components identified as being enriched for eye blinks or heartbeats were discarded as described below.

EEG data was collected using the Quick 20 EEG headset from Cognionics, Inc. (Carlsbad, CA), with sensor locations at F7, Fp1, Fp2, F8, F3, Fz, F4, C3, Cz, P8, P7, Pz, P4, T3, P3, O1, O2, C4, T4 in a monopolar configuration referenced to linked earlobes. EEG data were preprocessed for each team member using FieldTrip (Oostenveld et al., 2011) by applying high-pass (0.5 Hz) and low-pass filters (50 Hz) and removing bad channels (max = 2). Spatially transformed independent component analysis was performed with RUNICA (Delorme et al., 2012) to detect and remove artifacts associated with eye blinks, electrocardiogram and electromyogram activity. Following artifact rejection using RUNICA, data were back-reconstructed and the channels removed prior to RUNICA decomposition were interpolated back into the data by spherical interpolation. Frequency decomposition was performed by first segmenting data into 1 s epochs. The data were then windowed using Hanning taper and the frequency content of each trial was measured at 1 Hz intervals from 1 to 40 Hz using Fast Fourier Transform.

Team Neurodynamic Modeling

The goal of team neurodynamic modeling is to develop data streams that contain temporal information about the organization, function and performance of teams. In this study we highlight the 10 Hz frequency which is involved in attention and prioritizing stimuli (Klimesch et al., 2007; Klimesch, 2012), the 16 Hz frequency that is involved in action understandings (Hari, 2006), and the 40 Hz frequency involved in maintaining working memory and long-term memory encoding and retrieval (Roux and Uhlhaas, 2014; Bonnefond and Jensen, 2015). These frequencies were chosen based on prior work that revealed that these frequency bands had particular relevance for team neurodynamics (Stevens and Galloway, 2014, 2015).

As described earlier, the initial modeling step is to generate the power level vectors (i.e., −1, 1, and 3's) from the raw EEG data from each person, and create the *NS* for each second of the performance (**Figure 4**). The normalized power vector was presented to a previously trained artificial neural network and matching *NS* were assembled into a *NDS* which was updated each second with a new symbol (Stevens and Galloway, 2014). The structure (i.e., information) in these data streams was visualized by plotting the symbol expressed each second. By classifying the set of symbols over entire performances containing different segments (i.e., Briefing,

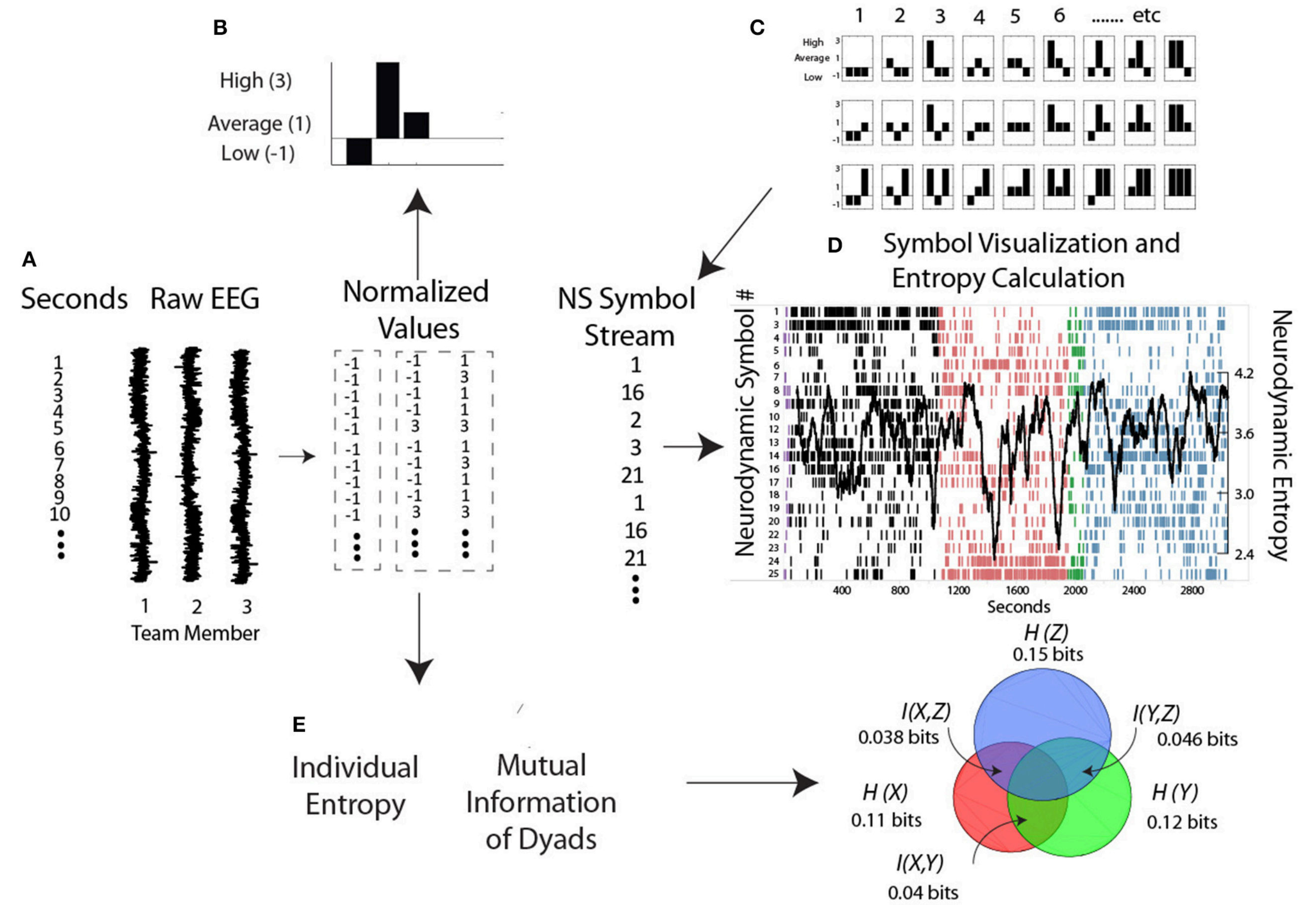


FIGURE 4 | Steps for generating and modeling neurodynamic data streams. (A,B) The raw EEG signals from each person are discretized each second into low, average, and high power levels and assembled into a *NS*. **(C)** The symbol matching the three person power vector is determined from the *NSS* lookup table and assembled into a *NDS*, where, **(D)** the symbols are visually mapped and a moving average of entropy calculated each second. **(E)** Levels of Individual Entropy and the Mutual Information of dyad pairs are calculated from the normalized symbols and used for subsequent team modeling as described in the text.

Scenario, and Debriefing segments shown by the different colors) the neurodynamic models generated encompasses a comprehensive set of task situations/loads (Fishel et al., 2007).

According to information theory, a data stream with 27 symbols has a theoretical entropy level of 4.76 bits if the symbols were equally distributed (i.e., a uniform distribution), and so if we observe a data stream to have an entropy of 4.58 bits, then we know that there is a "hidden" structure in that data, i.e., some symbols are expressed more frequently than others. But this difference does not tell us where the structure is, it only tells by how much. For that information the performance needs dividing into smaller time units like the Briefing, Scenario and Debriefing task segments or over even smaller time windows within these segments, i.e., an entropy rate. So if we determine the entropy over a 60 s or 100 s length segment and the entropy level is now 4.08 bits instead of 4.58 bits the new information we have gained is equal to the difference in *H* before and after we received that information, i.e., 0.5 bits. While it does not matter for the aggregated *H* levels, for practical teamwork purposes we need to know what symbols are lost, what symbols remain, and how they are distributed in the data stream, it is not sufficient to know just that some symbols remain or are gone.

Figure 4D is a plot of the 39 Hz (gamma) frequency bin from a healthcare team and shows several important features. In the Briefing (black) and Debriefing (blue) task segments the dominant symbols expressed were *NS* 1 and 2 representing times when most team members had low EEG gamma power. In contrast, the dominant symbols in the Scenario (pink) were *NS* 26 and 27 indicating times when most team members had high EEG gamma power.

It is important to note that high or low EEG power in the frequency bands is not necessarily good or bad, as different power levels serve different purposes; for example during spontaneous coordination the mu medial rhythm is synchronized (i.e., high power), but becomes suppressed or desynchronized (i.e., low power) during social interaction (Tognoli and Kelso, 2015). Similarly, synchronized (i.e., high power) alpha may provide a mechanism for selective attention while desynchronized alpha may promote working memory formation (Klimesch, 2012). It is also important to note that from a neurodynamic organization perspective, preferential expression of symbols representing high power or low power will show equivalent entropy levels if the variability of the symbols is the same. This is also shown in **Figure 4D** as large NS entropy decreases occurred when the gamma levels were either low (Briefing and Debriefing) or high (Scenario) across the team. Large entropy fluctuations identify performance periods warranting additional study through video and audio analysis, or semantic structure analysis.

Individual Entropy and Mutual Information

The next calculated variable is Individual Entropy (*IE*) (**Figure 4E**) where the normalized EEG values of each person are treated symbolically and then Shannon's entropy is calculated over a moving window as described above. It is not clear what Individual Entropy represents, although it can be thought of as the neurodynamic organizations of individuals as they perform their taskwork as well as their teamwork.

Short and long-term changes in NS_H identify fluctuating periods of team neurodynamic organization but they provide little information about possible neurodynamic synchronization among the team members and the possible roles of these interactions during teamwork; mutual information descriptions help supply this data. Mutual information (*MI*) is a measure of the mutual dependence of two variables, or how much knowing the value of one variable decreases the uncertainty of the value of the other. Mutual information was originally described in noisy channel communication as the information in the output channel that was present in the input channel, and has been widely used for evaluating information representations, transmissions, and content in single neurons and populations of neurons in stimulus- responses paradigms (Schneidman et al., 2003; Onken et al., 2014). We use *MI* to determine the amount of shared information between two team members, periods which we cautiously refer to as times of synchrony (Stevens and Galloway, 2016). Currently it is not known what the remaining information is after subtracting the *MI*. Possibilities include it being noise, or perhaps information more closely related to an individual's task work rather than teamwork.

The symbols used for calculating the *MI* of dyads were the same as for *IE* i.e., the normalized EEG vectors (−1, 1, and 3), and in all studies a moving average window approach for *MI* data reporting was used as described above for NS_H. An example of the relationships between *MI* and team entropy is shown in **Figure 5** for a submarine navigation team composed of six team members. In this figure there are five major events marked that were regarded as significant by the instructor. The individual colored lines in the *MI* plot represent the fourteen different dyad combinations of the team. The periods of elevated *MI* contained many of the dyad combinations suggesting that periods of synchrony are not always present, but when they are they involve many of the team members. The correlation between *MI* and NS_H was low ($r = 0.02$) at a time lag of zero indicating that while *MI* may be near periods of decreased NS_H, they may not always be the same periods.

RESULTS

Quantitative Models of Team Member Organization during Teamwork

This section provides examples describing how the different information flows in the neurodynamic data streams can be used to quantitatively:

1. Determine the degree of team synchrony as defined by mutual information.

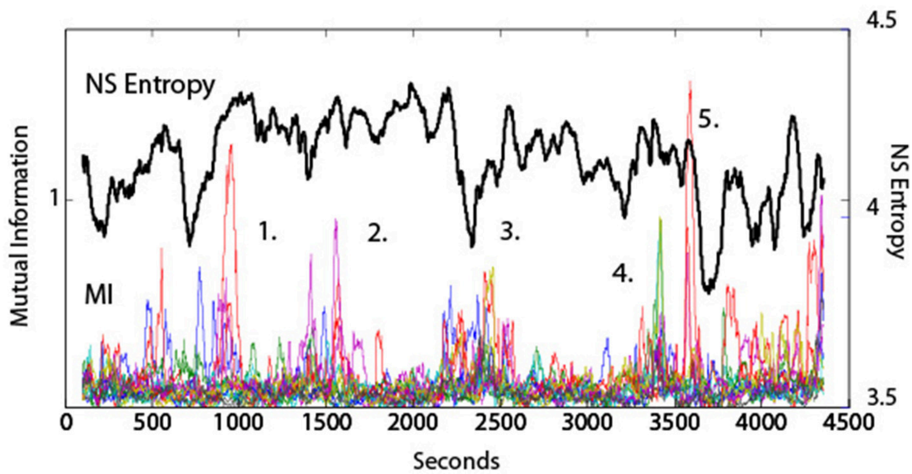


FIGURE 5 | Dynamical comparisons of NS_H and *MI*. The NS_H was averaged across all frequencies and all sensors, and the *MI* values were averaged across the fourteen dyad pairs shown by the colored lines. The numbers represent performance events surrounding those time periods. (1) The team was having difficulty remembering the sequence of buoys to use when establishing the ship's position. (2) The team was preparing for a turn into difficult waters with other ship traffic. (3) A simulation "Pause" was called by the Assistant Navigator to express his concerns with the team. (4) A Man Overboard event. (5) Beginning of the Debriefing segment.

2. Determine the contributions made by the individual team members to the overall team's neurodynamic organizations; and,
3. Dissect the momentary neurodynamics of individual team members to determine how these dynamics relate to the overall dynamics of the team and the task.

The studies in this section integrate NS_H dynamics, *IE* dynamics and *MI*, and introduce related information measures which are joint entropy (*JE*) and conditional entropy (*CE*). As illustrated in **Box 2**, *JE* is the sum of the *IE* of each team member, and *CE* is the entropy remaining after the *MI* between two persons is removed (shown in gray).

The first example shows the dynamical relationships among these variables for a Map Task performance (**Figure 6**). The modeling was performed with the CzP0 sensor bipole and is shown for the 10 Hz frequency. The *JE* profile for this performance was not uniform but showed decreases between 60 and 130 s, 140 and 200 s, and a broad decrease between ∼335 and 475 s. The profile of the *CE* showed larger decreases than the NS_H profile indicating the presence of shared 10 Hz information between the two persons. **Figure 6B** shows the dynamics of this shared information in the form of *MI*. *MI* is always a positive value and the *MI* profile was complementary to the difference between the *JE* and *CE* in **Figure 6A**. The *MI* accounted for ∼2% of the *JE* when averaged over the entire performance, and during the 60 and 130 s period and 140 and 200 s periods the proportion was enriched to ∼4 and 3% respectively.

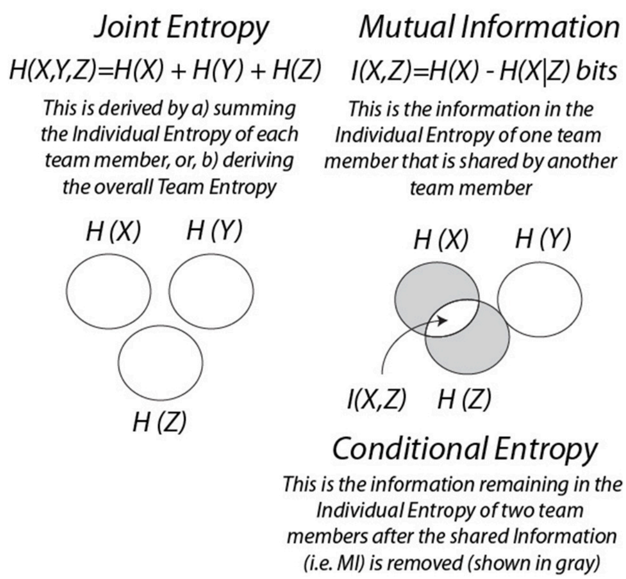
A more global view of team neurodynamics is shown by plotting the *MI* expression over time as a function of the EEG sensor location (**Figure 6C**), or EEG frequency bin (**Figure 6D**). Mutual information was detected throughout most of the performance at some sensor sites with the highest average *MI* levels found in the Fz, C3, C4, CzP0, and F3 sensors. There was minimal *MI* in the 3–8 Hz frequency bins while the highest *MI* levels were found in the 14–17 Hz bins.

The MT example indicated that quantitative relationships existed in the *IE* data streams of dyads and that it might be possible to do similar modeling between the members of larger teams. The relative levels of *JE* and *CE* compared with *MI* also suggested the presence of noise in the overall modeling approach. The next two examples address this issue using other properties of information theory.

One useful property of information theory is that information is additive: the information associated with a set of outcomes can be obtained by adding the information of individual outcomes. We use this property in the following way: Our hypothesis was that the entropy levels of each person reflected his/her neurodynamic organizational responses to the other team members and the task (plus additional background noises in the brain). An individual with three possible EEG power states (i.e., high, medium, low) would have a maximum entropy of 1.585 bits. For a three person team each with three possible states, the maximum number of symbols that could be expressed is 27 and the maximum information is $\log_2(27)$ or 4.755 bits. From the additive rule, the maximum information in three individual data streams should equal the information in a three person team i.e., ($1.585 \times 3 = 4.755$ bits). This additive rule provides a basis for comparing the amounts of neurodynamic organization of each team member and the contributions of individual team members' organization to the overall team's neurodynamic organization.

As shown in **Table 1** the average team entropy calculated when the team was modeled from the 27 symbol state space in **Figure 2A** was significantly lower than when the three *IE* levels were added together ($Mean_{IndEnt} = 4.44$ bits $\pm$ 0.18 vs.

BOX 2 | INFORMATION MEASURES



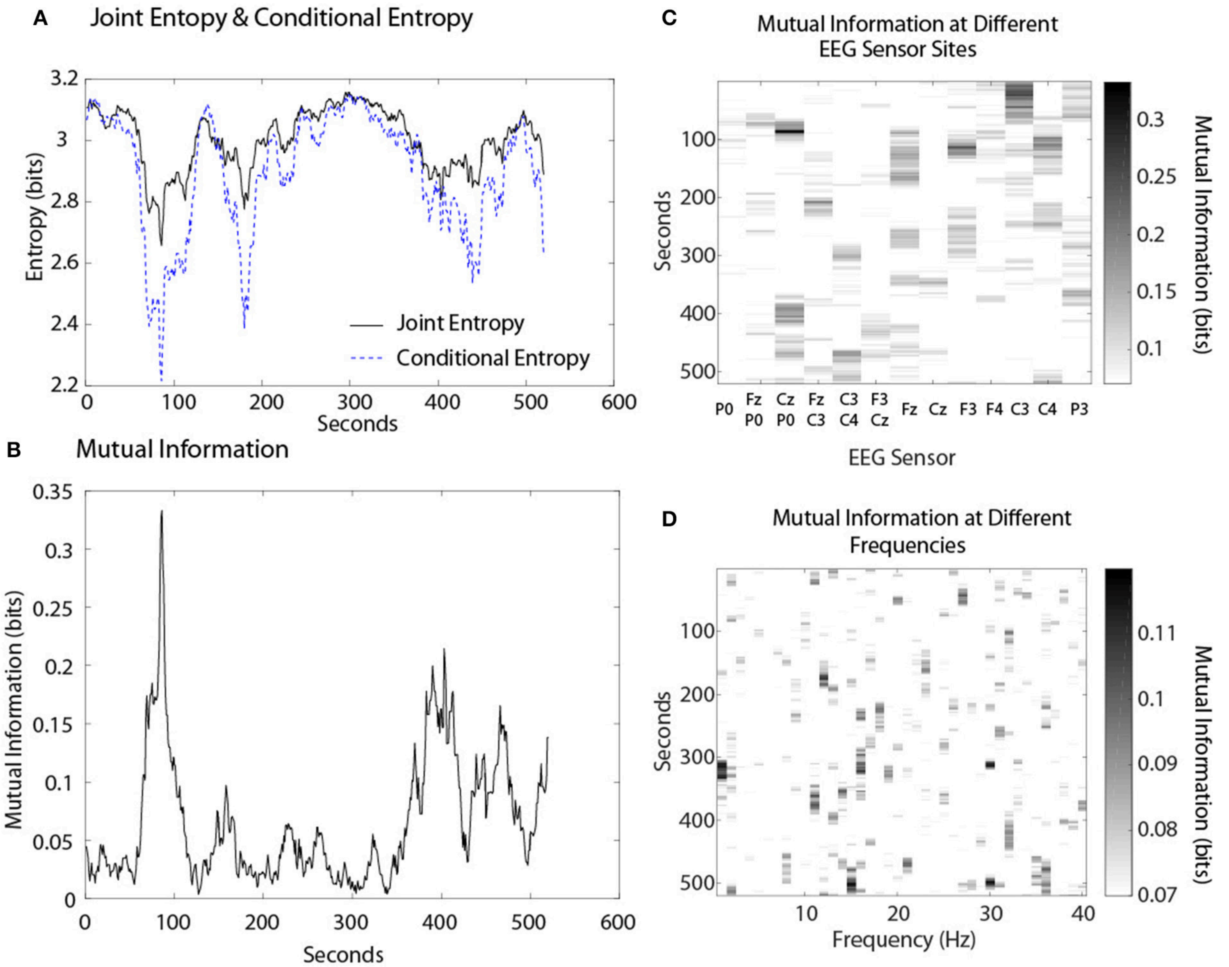


FIGURE 6 | (A) Dynamics of joint entropy and conditional entropy for a dyad performing a MT performance. **(B)** The mutual information of the same team. **(C)** The *MI* expression at different sensor sites. **(D)** *MI* expression at different frequencies.

TABLE 1 | Comparison of the entropy levels calculated by summing the IE of three team members or by directly modeling the NS_H using the 27 *NSS* in Figure 2A.

Team	Sum of IE	NS_H
1	4.44	4.12
2	4.22	4.01
3	4.35	4.15
4	4.53	4.27
5	4.21	3.94
6	4.68	4.37
7	4.68	4.41
Mean	4.44	4.18

$Mean_{TeamEnt} = 4.18$ bits $\pm$ 0.045 (*SD*), $t = 15.3$, $df = 4$, $p < 0.01$).

The reason for the difference is that the symbols in the *IE* data streams were divided equally into three groups and so the −1, 1, and 3 symbols were equally expressed. The 27 symbols in the NS_H were not similarly constrained and some symbols are repeated more frequently than others as part of the natural rhythm of the team on the task. This decreased variability differs on a frequency and sensor specific basis and results in a lower entropy levels. These relationships are shown in **Figure 7** for the 10 Hz frequency bands from the C4 (**Figure 7B**) and F3 (**Figure 7D**) sensors and the 40 Hz frequency band from the C4 sensor (**Figure 7C**). As expected from the modeling protocol, the three-level normalized symbol stream had equal numbers of the −1, 1, and 3 symbols (**Figure 7A**), while the *NDS* from the different sensors and frequency bands showed variable symbol distributions.

The unequal symbol expressions seen after randomizing the *NDS* may indicate and important organization property of teams. One idea is that the task demands encourage/select particular neurodynamic relationships across the members of a team. To the extent these symbols are consistently associated across team activities or teams (novice/expert for instance) they may indicate important team member relationships relative to the task demands. We term the entropy associated with these

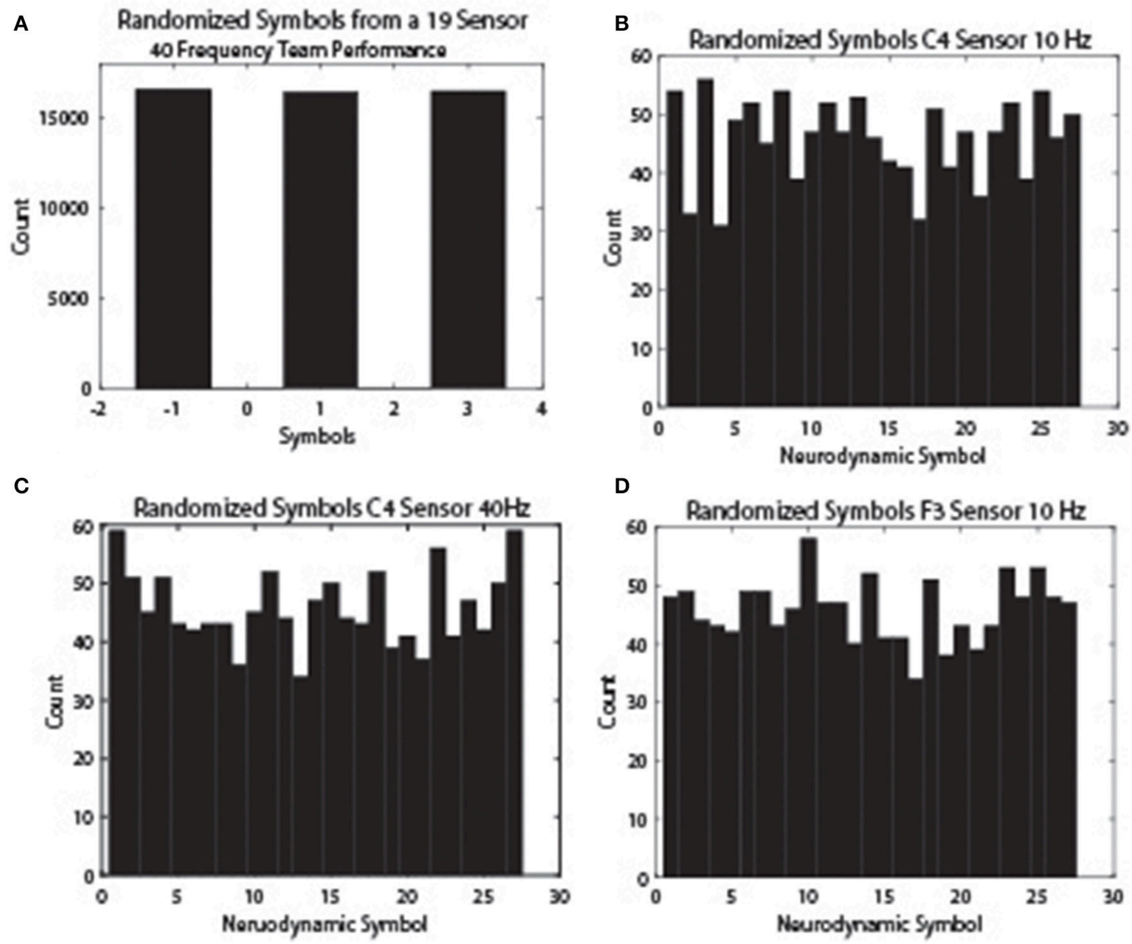


FIGURE 7 | NS distributions across EEG frequency and sensor sites. The neurodynamic symbol streams were randomized to remove temporal structures and histogram plots were prepared to show the NS distributions. **(A)** The distribution of the −1, 1, and 3 symbol categories for a team performance. **(B)** The symbol distribution of the 10 Hz frequency band from the C4 sensor. **(C)** The symbol distribution of the 40 Hz frequency band from the C4 sensor. **(D)** The symbol distribution of the 10 Hz frequency band from the F3 sensor.

symbol distributions the Task Entropy, or H_{Task}. With these considerations, the sum of the individual entropy from the team members is used in the following sections when calculating the proportion of time team members are synchronized with each other using *MI*.

Submarine Navigation Team

The next example was a three-person navigation team that performed a required submarine piloting and navigation simulation exercise. In an effort to remove unwanted noise from the modeling we subtracted the *IE* from the entropy of frequency and sensor-matched *IE* that had been randomized before the entropy calculations. We term the resulting value Neurodynamic Organization when applied in a team context, and abbreviate it ND_{Ω}. This resulted in positive values that could be directly compared with *MI* (**Figure 8**); the dynamics of the ND_{Ω} and *MI* data streams are shown in **Figures 8A,B**.

Figure 8C shows the ND_{Ω} for the Assistant Navigator (ANav), the Quartermaster (QM), and the Navigator (Nav) and the circles are proportional to the overall levels of individual ND_{Ω}. The overlap of the circles in the Venn diagram represents the levels of synchrony (as measured by *MI*) among the three team members, and the levels are labeled below. Removing the "noise" in the *NDS* by subtracting the *IE* of each person from randomized values of frequency and sensor matched *IE* streams resulted in higher proportions of *MI* being detected across the team members, as compared with the *MT* studies, being as high as 17% between ANav-NV when averaged across nearly 2 h. of teamwork.

Healthcare Teams

The final example extends these ideas by providing a more dynamical perspective of IE in relation to the ND_{Ω}. The healthcare simulation illustrated in **Figure 9** was designed to induce uncertainty/surprise in the team as it involved a patient undergoing an operation where shortly after anesthesia was

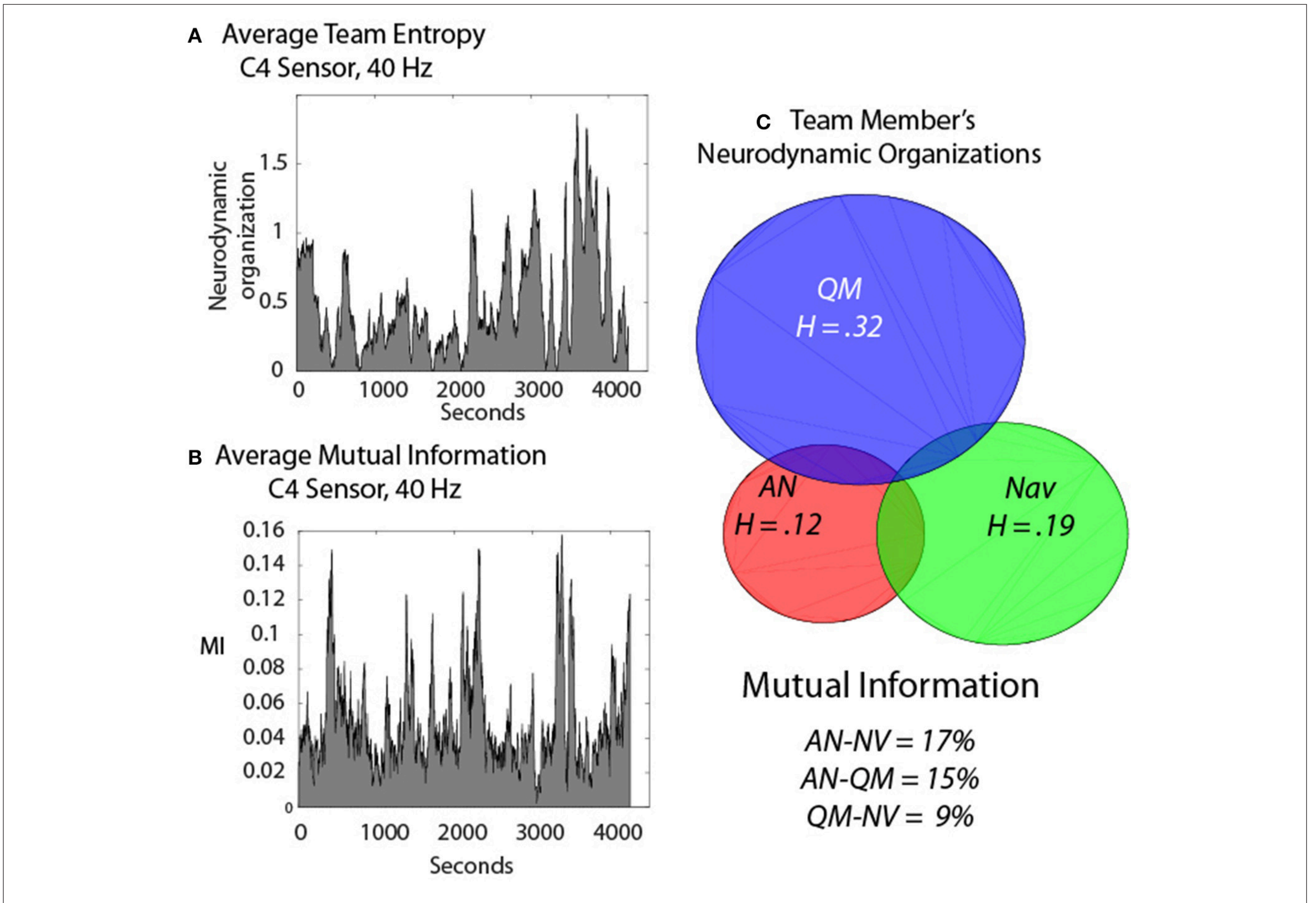


FIGURE 8 | Neurodynamics of a three-person submarine navigation team. (A) The Neurodynamic Organization profile of the summed *IE* **(A)** or *MI* **(B)** from the Assistant Navigator (AN), the Quartermaster (QM) and the Navigator (NV) during a simulated navigation exercise. **(C)** Venn diagram of the individual IE levels and the degree of team synchrony determined by the *MI* of the dyads.

induced the team had to evacuate the operating room with the patient due to a fire. The figure shows the *IE* traces for the anesthesiologist (red), scrub tech nurse (green), and a registered nurse (blue). The low ND_{Ω} just prior to the fire rose and continued to rise for each team member until the end of the simulation indicated by the solid line. As the team adjourned to the Debriefing room the ND_{Ω} returned to lower levels. The sum of the three team member's *IE* closely paralleled that of the team neurodynamic entropy (i.e., NS_H) modeled from the 27 symbols in **Figure 2A**. The mutual information between the different dyad pairs is shown in the Venn diagram in relation to the summed *IE* levels of the three team members. The % of the individual entropy that was *M*I was highest, 62% for the AN and ST, 29% for the AN & RN, and 10% for the ST and RN.

DISCUSSION

In this study we have used information-organization concepts to develop metrics for the quantitative neurodynamic modeling of team performance. After beginning from a theoretical perspective of a perfect team, we highlighted team performances of three tasks that were very different in their content domains and team compositions.

The first example with high school dyads showed the relationships between the neurodynamic organizations as measured by NS_H and synchrony of the team as measured by *MI*. It further illustrated that while there was some redundancy in *MI* expression at different scalp positions, the different EEG sensor data provided different perspectives of the performance; similar ideas apply to the EEG frequency data as well.

The second example with a submarine navigation team introduced comparisons between individual NS_H and *MI* for the dyad combinations of a three-person team and provided quantitative estimates of the proportion of neurodynamic organization that might represent synchronization (as measured by *MI*) for each team member as well as the degree of (neurodynamic) interactions among the different team members. The third example expanded these ideas for a healthcare team and dynamically illustrated the changing *IE* relationships among the team members.

The innovative feature of this modeling process is the transformation of the physical units of the raw EEG power

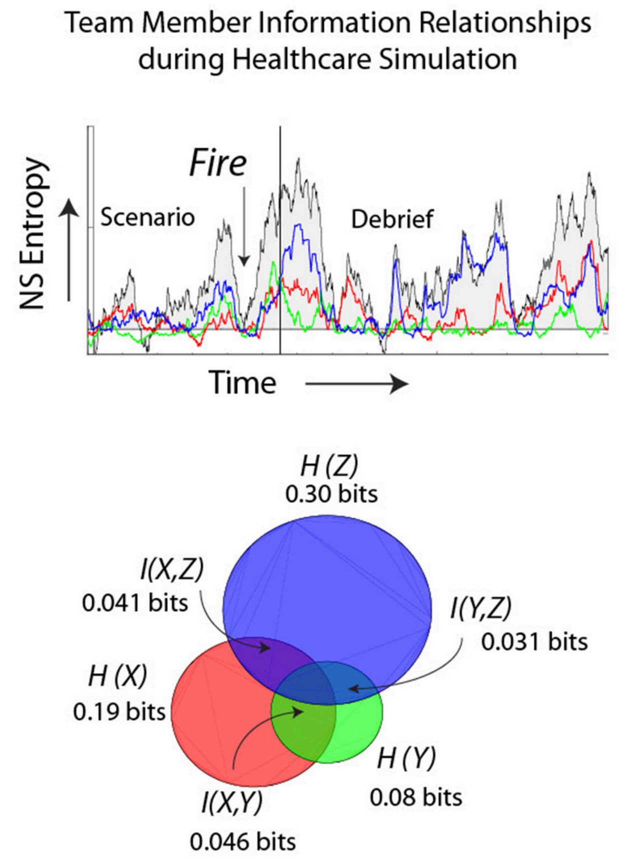


FIGURE 9 | Dynamics of a healthcare team during a simulated fire in the operating room. The individual entropy levels were calculated using the normalized frequency-specific data symbols (i.e., −1, 1, 3) over a moving window of 60 s. The colored traces show the *IE* entropy remaining when the team members' entropy were subtracted from parallel frequency-matched entropy from data streams that were randomized before calculating entropy. The background trace is the team ND_{Ω}. The lower Venn diagram shows the *IE* for the anesthesiologist (AN), registered nurse (RN) and the scrub tech nurse (ST). The *MI* of the dyad pairs are shown in the overlapping regions.

(in microvolts) from different team members into a single symbolic information stream where the symbols represent the relationships of the different team members with each other and with the second-by-second evolution of the task. At the junction of this transformation two modeling pathways result: (1) the raw EEG power levels that can be analyzed at scales of 2 s or less for dynamics that relate to mental imagery, social coordination, emotions, etc.; (2) and the entropy levels (bits of information) of the neurodynamic organizations in the symbol streams that relate more easily with other information measures like the organization of speech or the behavioral organizations recognized by experts as proficiency. This transformation provide a teamwork link analogous to the connection between thermodynamics and information theory in individuals detailed by Collell and Fauquet (2015).

The results to date suggest that higher performing teams are those characterized by more variability (i.e., higher entropy levels). The most interesting data streams to study though for understanding how to assemble, train and support teams might be those with less variability (i.e., lower entropy levels). These periods are often seen associated with stress or uncertainty, and when teams develop new neurodynamic organizations as they seek to acquire/synthesize additional information (Stevens et al., 2013, 2016a).

The similar findings with three different tasks suggests that the variables we are studying, and their resulting dynamics, may be a fundamental property of teams performing complex tasks. If so, this line of research has the potential to inform many practical applications related to team performance and resilience, as well as foster the development of new theoretical understandings about physiological synchronizations associated with social coordination and teamwork.

The principle driving this line of research is that teams adopt a more organized configuration, neurodynamically speaking, when seeking new/different information and organizations to balance the demands of the changing environment. When these challenges/uncertainties are resolved the team once again restructures to adopt a more efficient configuration; it may or may not be the same organization as before the perturbation. The length of these periods can be seconds, or much longer depending on the nature of the "surprise" experienced and the amount of new information that has to be acquired, synthesized, and exchanged before the team can return to a normal operating mode. These dynamics are consistent with the multifractal scaling in *NDS* previously seen in the neurodynamic data streams of submarine teams (Likens et al., 2014). The across sensors and frequencies *IE* and *MI* variability in **Figures 6C,D** may provide one explanation for the multifractal structures seen in those studies.

The three examples also hint at the dimensionality challenge of team neurodynamic modeling. Information theory is fundamentally about signals, not the meaning they carry; linkages to more human—understandable measures are needed to extract what the neurodynamic organizations/synchronizations "mean" to a team. This contributes to the dimensionality problem. As an example, with 19 EEG sensors and 40 (1 Hz) frequency bins, there are 760 sensor x frequency combinations per person to model over tasks lasting 500–4,000 s or more. The data streams include raw EEG data, data symbols, individual entropy, joint entropy conditional entropy, mutual information and team entropy, each of which has different properties/uses. Additionally, real-world, complex tasks often include segments with very different team requirements (i.e., Briefing, Scenario, Debriefing), along with shorter periods of organization relating to the momentary demands of the task. For validity and relevance, other measures are needed like speech flow, or speech content, instructor ratings and/or sub-dimensions of ratings like dialogue, problem solving, teamwork, etc. The additional measures may not always provide increased clarity. In a recent study the cross-level effects between the dynamics of communication and neurodynamics were modeled (Gorman et al., 2016). One interesting findings was a difference in the temporal lags between the neural and communication data streams between novices and experts, indicating that relating variables to each other at zero time lag may be insufficient to understand the interrelated system dynamics, and that changing time dimensions may also be needed during modeling.

More optimistically, the cross-couplings in that study also showed that redundancy exists between speech and neurodynamics. Similar redundancies are also seen between nearby EEG frequency bands, and also across EEG sensor sites, and so only a subset of the theoretical combinations of the above variables will be needed to encompass the major fundamental interactions among team members (Carandini and Heeger, 2012).

In several small-scale studies we have approached this modeling complexity by linking behavioral observations with neurodynamic organization measures (Stevens et al., 2015, 2016c, 2017). Currently, most evaluations of teams performing natural tasks rely on experts who observe and rate teams across important, but quantitatively vague dimensions like leadership, team structure, and situation monitoring using vetted rubrics. One widely used evaluation rubric in healthcare is the TeamSTEPPS® program which was developed by the Department of Defense for evaluating teams across dimensions that are prevalent in healthcare, but common to many professional teamwork situations (Baker et al., 2009). A more recent instrument, the Submarine Team Behavior Toolkit (STBT), focuses on team resilience and was designed for evaluating training and on-the-job teaming in the submarine force (described in Stevens et al., 2015). These scales tend to rely on macro features of team performance by summarizing observations over extended periods of time. While the shorter-term dynamics of the team are implicitly acknowledged in the resulting ratings, the dynamical details are often lost.

In an earlier study we proposed a bell-shaped relationship between what we then termed cognitive organization and team performance (Stevens et al., 2013). The cognitive organization was based on NS_H where the lower the entropy the more neurodynamically organized the team. These organizational/performance relationships were illustrated by plotting transition matrices of the *NDS* symbols at times *t* vs. *t+1 s*, and doing so for teams of different experience. Teams experiencing stressful situations showed the greatest degree of neurodynamic organization, followed by teams with some experience engaged in advanced training. At the other end of the curve were teams with little domain knowledge or experience; these were the least organized teams. Experienced teams were shown at the top of the curve, a balance of flexibility and organization (**Figure 10A**).

A restructured version of this model is shown in **Figure 10B** which more empirically encompasses our understandings of NS_H levels during teamwork. The asymptotic shape of the curve reflects the relationships between the information (NS_H) and the number of symbols in the data stream. At the high end of the curve, some high performing teams have approached the theoretical maximum entropy levels while the lowest level of NS_H we have observed reflects a team using only 3–4 symbols of the 27-symbol *NSS*. This range provides a relatively broad range of the curve over which to use information measures to probe team dynamics and performance.

Expressed in terms of neurodynamic organizations (ND_Ω), this would represent levels of 0 to $\sim$ 1.5 bits. What does this bit or so of information tell us about the past, present, and future of the data stream? When thought of in terms of a single observation, if the sequence is a series of alternating 1's and 0's it tells us everything, while if the series contains random 1's and 0's it tells us very little (James et al., 2011). From the transition matrices in **Figure 10A**, one observation will likely tell us quite a lot. The existence of the diagonal in the $t -> t+1$ transition matrix of Experienced Teams indicates that the *NDS* has long memory, the statistical dependence of two points with increasing time intervals, a property shared by many real-world data time series (Palva et al., 2013). Furthermore, the thickness

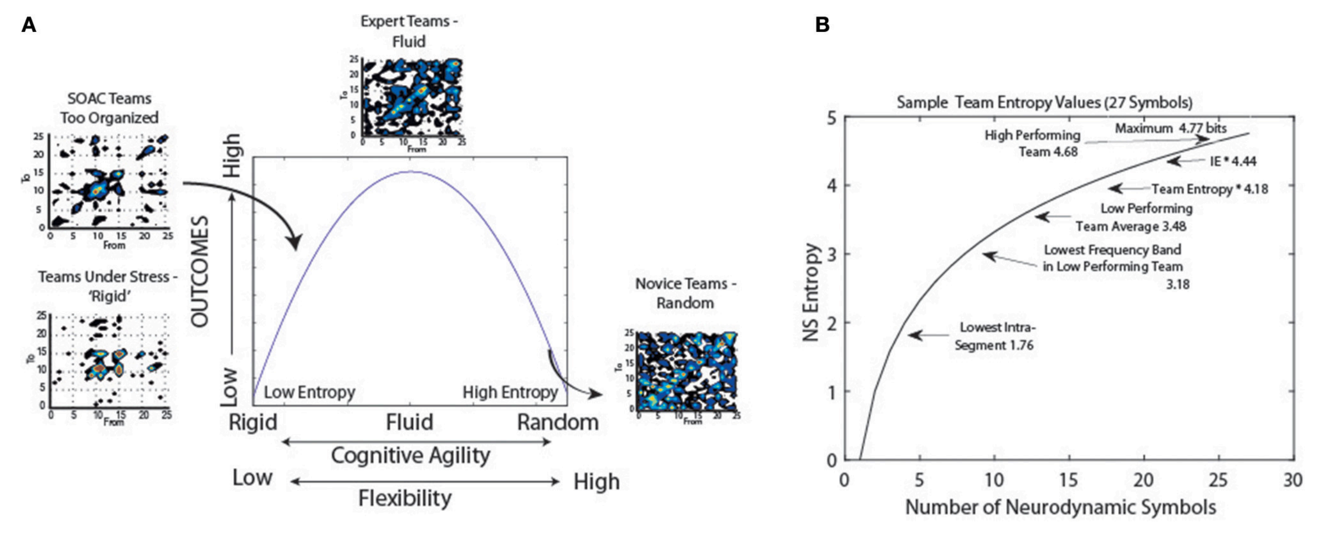


FIGURE 10 | Models of neurodynamic organizations. (A) Prior neurodynamic organization model (Stevens et al., 2013). **(B)** Plot of the entropy levels as a function of the number of symbols. The labels position levels of different teamwork functions.

of the diagonal tells us that the next symbol in a sequence may not be exactly the current one, but one closely related on the 27 symbol topological *NSS*. So short term-we learn a lot from a single observation. This will be particularly true for teams in training who have some experience and are refining their skills; the team in **Figure 9A** highlighted as having moderate organization. The challenge will be that the most novice teams will have very high levels of entropy and may be indistinguishable from noise, or more problematically, very experienced teams.

Finally, in the Introduction we posed the questions: (1) Can we begin to populate models of teamwork with quantitative data that reflects what is understood to be expertise? (2) Are teams in fact fully connected, and if so, how tightly linked are the couplings across different team members and different teamwork measures? (3) Are there preferred couplings among team members depending on the task, or training protocol, or training site, and does this make a difference? (4) How closely related are the models being revealed by neurodynamics, communication and behavioral measures. From the findings reported in the Results we feel these questions are all approachable.

One important relationship reported in this paper is that between the *IE* of the team members and the *MI* between dyad pairs of the team. For the first time it is possible to put quantitative relationships between the dynamics of each team member during the task, along with the neurodynamic interactions between the members of the team. While the three-person examples in **Figures 8**, **9** show the aggregated couplings among team members it is an easy extension to develop dynamic networks that show momentary relationships. These dynamical models enable comparisons with measures of team communication (Gorman et al., 2016) as well as behavioral models derived from expert raters (Stevens et al., 2015, 2016c), leading to dynamic multi-level, multi-modal and multi-entity snapshots of novice and expert teams in action.

We therefore see the further development of these methods (in particular, to consider the information provided by many spatial and temporal scales simultaneously), as an important area for developing the computational neuroscience of teams for some years. We also see increased opportunities to restructure team training. To the extent that neurodynamic organization equates to individuals and teams experiencing and resolving uncertainty (Stevens et al., 2016a) it may provide an indicator of where training should be focused.

AUTHOR CONTRIBUTIONS

All authors listed, have made substantial, direct and intellectual contribution to the work, and approved it for publication. The authors jointly developed the design, performed the neurodynamic analyses, and wrote the paper.

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How Do Soccer Players Adjust Their Activity in Team Coordination? An Enactive Phenomenological Analysis

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This study examined how individual team members adjust their activity to the needs for collective behavior. To do so, we used an enactive phenomenological approach and explored how soccer players' lived experiences were linked to the active regulation of team coordination during eight offensive transition situations. These situations were defined by the shift from defensive to offensive play following a change in ball possession. We collected phenomenological data, which were processed in four steps. First, we reconstructed the diachronic and synchronic dynamics of the players' lived experiences across these situations in order to identify the units of their activity. Second, we connected each player's units of activity side-by-side in chronological order in order to identify the collective units. Each connection was viewed as a collective regulation mode corresponding to which and how individual units were linked at a given moment. Third, we clustered each collective unit using the related objectives within three modes of regulation—local (L), global (G), and mixed (M). Fourth, we compared the occurrences of these modes in relation to the observable key moments in the situations in order to identify typical patterns. The results indicated four patterns of collective regulation modes. Two distinct patterns were identified without ball possession: reorganize the play formation (G and M) and adapt to the actions of putting pressure on the ball carrier (M). Once the ball was recovered, two additional patterns emerged: be available to get the ball out of the recovery zone (L) and shoot for the goal (L and M). These results suggest that team coordination is a fluctuating phenomenon that can be described through the more or less predictable chaining between these patterns. They also highlight that team coordination is supported by several modes of regulation, including our proposal of a new mode of interpersonal regulation. We conclude that future research should investigate the effect of training on the enaction of this mode in competition.

Keywords: enactive approach, phenomenological data, elicitation interviews, interpersonal coordination, indirect interpersonal coordination, soccer, collective body memory

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INTRODUCTION

We often take delight in following a fast counterattack in a soccer game, listening to a string quartet, or watching a dance troupe improvising: the wonder is how the multiple social agents manage to coordinate their actions so quickly and suitably. Team performances require the coordinated contributions of two or more members working interdependently to achieve a common objective (e.g., Salas et al., 1992). The key word is coordinated, as this is what determines the result. But for sports psychologists, understanding exactly how team members' actions are successfully coordinated has remained a challenge (e.g., Blickensderfer et al., 2010; Bourbousson et al., 2012; Travassos et al., 2012).

A recent review identified three main theoretical perspectives to explain interpersonal coordination (see Araújo and Bourbousson, 2016). The first is the social-cognitive perspective (e.g., Eccles and Tenenbaum, 2004; Reimer et al., 2006; Blickensderfer et al., 2010), which assumes that through practice and experience team members develop mental representations of the performance environment (also depicted as mental models or knowledge) within which the team members regulate their behaviors to achieve high performances (e.g., Eccles and Tran Turner, 2014). For instance, these mental representations allow team members to predict events or understand the operations being undertaken by the other team members with whom they are interacting (Blickensderfer et al., 2010). According to this approach, to achieve team coordination, a subset of each team member's mental representations must be similar to at least a subset of the mental representations of the other team members, such that each team member can form clear expectations about the others' actions (e.g., Eccles and Tenenbaum, 2004). They then coordinate by adapting to the dynamic changes in the competitive performance environment and by selecting appropriate goal-directed actions to execute at appropriate times (Eccles, 2010).

The second is the ecological dynamics perspective (e.g., Travassos et al., 2012; Silva et al., 2013; Passos et al., 2016), according to which the player's activity is not based on mental representations stored in memory but rather on the perception of surrounding informational constraints. For example, the perception of a basketball defender's most advanced foot might prompt an attacker to drive the attack to that side (Esteves et al., 2011). These surrounding constraints provide players with direct possibilities for acting within the performance environment. The players thus regulate their behaviors through the perception and use of these affordances. At the interpersonal level, through practice, players can become perceptually attuned to the affordances *of* others (i.e., what actions another person affords the perceiver) and the affordances *for* others (i.e., what actions are possible for another person) during competitive performance (Fajen et al., 2008). This allows them to undertake more efficient actions by functionally adjusting their behaviors to those of their teammates and opponents.

The third is the enactive perspective (e.g., Poizat et al., 2009; Bourbousson et al., 2012; Gesbert and Durny, 2017), according to which a team member's activity is based on the process of making meaning. By acting in direction of the other players, he/she feels sensations and makes sense of the players' behaviors that allows him/her to develop a higher order understanding of the situation. Based on what is relevant to the team member in relation to his activity, he/she will be more or less attuned to environmental information. For instance, in a defensive phase, four basketball players may focus on their direct opponent, whereas the fifth thinks that this opponent is not dangerous and chooses instead to observe the game (see Bourbousson et al., 2012). Players actively and asymmetrically regulate the conditions of their exchanges with the environment (e.g., Barandiaran et al., 2009; Froese and Di Paolo, 2011)—they look for and select what is relevant for them to act in the environment. At the interpersonal level, this means that team coordination is dynamically achieved in real time and cannot be prescribed by previous shared knowledge. The study of team coordination phenomena from this perspective refers to the extent to which individual activities contribute to or perturb the activity of others. It notably implies exploring how the meaning that each team member builds in her activity corroborates the meanings simultaneously built by the teammates (i.e., participatory sense making). For instance, in the study of Bourbousson et al. (2012), four players share meanings about the monitoring of their direct opponent but not the fifth player. Despite the recent advances, this conceptualization remains relatively neglected, as noted by Bourbousson and Fortes-Bourbousson (2016). In general, the objective is to determine how individual team members adjust their dynamic involvement in team coordination online and how the other team members simultaneously join in. The involvement means the concerns enacted by each player at a given moment, that is to say what he/she wants to do at a given moment. In the present study, we sought to address these research questions by adopting an enactive approach.

A first study has addressed these questions using an intermediary methodology. For instance, Millar et al. (2013) studied how interpersonal coordination was achieved and maintained in two-person rowing boats by interesting to the experiential knowledge built and used by expert rowers to coordinate during race. They conducted semi-structured interviews (i.e., qualitative methodology) with nine expert rowers and paid close attention to the perceptual information underlying the interpersonal coordination and how the information were used. Their results showed that the expert rowers coordinated their actions without taking each other into account, but rather by being attuned to variations in the boat speed. The authors thus developed the notion of extrapersonal coordination to describe how two rowers manage to achieve tight coordination by articulating their respective activities around an indicator in the situation (i.e., the variation in boat speed).

More recently, other studies have also addressed these questions using an enactive methodology. For instance, R'Kiouak et al. (2016) investigated how two coxless rowers experienced the effectiveness of their joint action during a race. The authors conducted individual self-confrontation interviews with each rower post-race to collect phenomenological data. From these data, the authors reconstructed the dynamics of the lived experience of each rower during the complete race by identifying the chaining of experience units across time. Each of these units is composed of six elements of meaning: current action (i.e., physical action or an interpretative act), involvement (i.e., the individual's concern at a given moment), expectations, prior mobilized knowledge that is relevant to the current situation, perception (i.e., elements of the situation significant to the individual at a given moment) and refashioned knowledge. A detailed examination of these elements of meaning then allowed them to characterize how each rower experienced the joint action effectiveness. Three typical modes of experiencing joint action effectiveness were characterized (i.e., meaningless, effective, and detrimental). The authors then synchronized the rowers' typical experiences in order to examine how the rowers simultaneously and similarly experienced the effectiveness of their joint action during the ongoing performance. Their results indicated that the rowers could experience the joint effectiveness of their joint action as detrimental, effective or divergent. This highlighted the use of an interpersonal regulation mode based on direct co-regulation between the rowers. But their results also indicated that the rowers could not have a meaningful experience of their joint action (i.e., they did not pay attention to the joint action at the level of their activity). This result shed light on the use of an extrapersonal regulation mode based on the adjustment of the rowers' movements in response to information from the boat and the reaction of the water which rowers were attuned. Their results thus indicated that interpersonal coordination was not the constant focus of the rowers' active adaptations. While acting on their oar, the rowers were particularly able to adjust their movements in response to the boat information and the reaction of the water, which allowed them to respond similarly (i.e., extrapersonal regulation mode). The authors then asked several research questions: (a) How might these two modes of regulation co-occur during a given ongoing joint action? (b) What setting characteristics are propitious for one of these regulation modes to emerge? and (c) How actors switch dynamically from one regulation mode to another during an unfolding joint action?

The questions were again raised in the work of Bourbousson and Fortes-Bourbousson (2016), who also highlighted the limited number of studies investigating how team members actively adjust their interpersonal coordination in real time. Although the studies in the sports sciences on the regulation modes enacted by team members have essentially dealt with the rowing dyad, one study investigated how basketball players heed their teammates in the first 10 min of a championship match (Bourbousson et al., 2010). To do so, the researchers filmed a match and then conducted individual self-confrontation interviews with each player. These interviews provided verbalization data on the teammates that each player took into account at a given instant in order to act. Their results showed that, at the level of activity that was meaningful for them, the basketball players most often took a single teammate into account. In cases of one-on-one play, however, sometimes no teammate was taken into consideration. The results also revealed that only 13% of the coordinations were reciprocal and that therefore the network of connections was for the most part built of one-directional cognitive links. These results cast doubt on the long-held assumption of the need for a co-regulation mode among team members in order to coordinate. According to Bourbousson et al. (Bourbousson et al., 2010; Bourbousson and Fortes-Bourbousson, 2016), these co-regulation modes may occur only between certain teammates, with the team then functioning on the basis of these few coordination links. The results also raised questions about the regulation modes enacted by members in the case of bigger social systems (i.e., a team sport).

This study sought to respond to these questions by investigating the regulation modes enacted by soccer team members in order to play with tight coordination during a match. In the research cited above, special attention was given to how the agents experienced their ongoing activity and regulated team coordination. This has been one of the pillars of the enactive approach since Varela's work (e.g., Varela et al., 1991; Di Paolo et al., 2010; McGann et al., 2013). Activity is the process of making meaning between an autonomous agent (e.g., a soccer player) and the environment. By actively and asymmetrically regulating the conditions of the exchange with the environment, he/she builds meaning and enacts her *own-world* (Di Paolo et al., 2010). This own-world is how he/she experiences her own coupling with the environment in the moment (Thompson, 2007) that is, through what is, at that very moment, relevant to him/her in relation to his/her activity. For instance, what is he/she trying to do? What is drawing his/her attention? What is he/she feeling? What made his/her decide something? The situated experience lived by agents is therefore not considered as epiphenomenal, as in other theoretical approaches (e.g., Blickensderfer et al., 2010; Araújo and Davids, 2016), but instead requires phenomenological investigation (Varela et al., 1991; Thompson, 2007). The methods used in this approach are retrospective phenomenological interview techniques that can be brought together under the *first-person* approach method (e.g., Varela and Shear, 1999), in the aim of capturing team members' lived experiences at the level of their prereflective consciousness in situation through verbal description (Legrand, 2007). An enactive phenomenological analysis always gives primacy to individual subjectivity and then describes the team coordination. The analysis describes how players' experiences are arranged and then determines how these arrangements are adjusted over time (e.g., Poizat et al., 2009; Bourbousson et al., 2012; R'Kiouak et al., 2016; Gesbert and Durny, 2017).

The aim of the present study was to describe how soccer players adjusted their activity online to the need for collective behavior during competition. To do so, we used an enactive phenomenological approach to explore how the players' lived experiences were linked in the active regulation of team coordination during offensive transition situations.

METHODS

Setting and Design of the Study

The present study was carried out in collaboration with the Performance Unit of Stade Rennais Football Club (a top tier French professional soccer club) throughout one season. The aim was to describe and better understand the ongoing interpersonal coordination during offensive transition situations. These situations are defined as a passage of play in which a team switches from defense to offense following a change in ball possession. In the offensive phase, the team's aim is to create and exploit open areas in order to penetrate the opponents' defense and ultimately open up opportunities to score a goal (e.g., Grehaigne et al., 1997; Bangsbo and Peitersen, 2004). In contrast, in the defensive phase, the team's aim is to deny time and space to the opponents with the ball in order to prevent their goal scoring opportunities (e.g., Grehaigne et al., 1997; Bangsbo and Peitersen, 2002).

For a number of technicians, the fast transition from defense to attack is one of the keys to success in modern soccer (e.g., FIFA, 2014). Coaches' analyses of the latest international competitions have taken note of several strategies that teams use to gain the ball and then attack the opponent goal (FIFA, 2010, 2014; UEFA, 2012). In the defensive phase, for example, the team might go after the opponent players in the most forward positions on the field and then aggressively put pressure on the ball carrier and his nearby teammates through well-coordinated horizontal and vertical movements. Once the ball is recovered, quickly moving to the opponent's midfield and split-second timing of the last pass seem to be the crucial next steps in the counterattack. To summarize, a soccer team must coordinate its actions to regain and quickly move the ball into the scoring zone.

Although coaches tend to consider the offensive transition a crucial moment in high-level competitive soccer, few studies to our knowledge have examined how players in competition experience this situation in real life. Such situations usually involve many players (a) sharing *a priori* a mutual objective (i.e., win the match), (b) having few opportunities to explicitly communicate about the future action, and (c) having little time to exploit open areas after recovering the ball in order to score. We therefore assumed that this setting would offer an opportunity to enrich the current perspectives on team coordination in a dynamic task context (Fiore and Salas, 2006).

Participants and Procedure

Fifteen French male soccer players and their coach volunteered for this study. The participants were 17 years old at the time of the study ($M = 17.40$ years old, $SD = 0.3$) and had all been playing soccer for 10 years. All the players had played and trained together for at least a year and a half ($M = 3.75$ years, $SD = 1.94$). They played in the top tier of France's under-19 category. This study was carried out in accordance with the Declaration of Helsinki. It was approved by a local Institutional Review Board of the Rennes 2 University. The players were informed of the study's purpose and were told that participation was entirely voluntary. Before the study began, players, their families, and the principal researcher approved a protocol agreement that described the study's purposes in detail and ensured player confidentiality (i.e., players were given pseudonyms). More precisely, players and their families provided written informed consent.

A Stade Rennais staff member filmed eight championship matches from the stand, mainly using a wide-angle shot focusing on the player on the ball. These matches were the material from which the offensive transition situations were extracted. This extraction process was carried out by the first author, who also holds a Union of European Football Associations (UEFA) A coaching license. Each offensive transition situation met two criteria: (a) ball recovery occurred between the halfway line and midway into the opponent's half and (b) the players had to have an opportunity to attack their opponent's goal. A total of eight offensive transition situations (defined in the following sections as S1, S2, up to S8), each lasting an average of 20 s, were extracted.

Data Collection

Two types of data were gathered: (a) continuous video recordings of the players' behaviors during competition and (b) verbalizations from post-match interviews.

A Stade Rennais staff member filmed eight championship matches from the stand, mainly using a wide-angle shot focusing on the player on the ball. This gave a continuous view of all the players involved in the offensive transition situations. By involved, we mean a player who participated in winning the ball back and the subsequent attack on the opponent's goal, either as the player on the ball or a player offering him a pass option to move the ball toward the goal. In the present study, the eight offensive transition situations involved two or three players (i.e., six situations with three players and two situations with two players). Once an offensive transition process was identified, elicitation interviews were conducted with the players involved.

Verbalization data were gathered from the elicitation interviews carried out with the players involved in each offensive transition situation. These interviews were conducted 48 h after competition and were preceded by a brief self-confrontation interview (e.g., Hauw and Durand, 2007) that consisted of showing the player the video of the extracted situation that had allowed us to identify the units of activity he had experienced from his own point of view (Zacks and Swallow, 2007; Kurby and Zacks, 2008):

> "... When I saw Phil get the ball, I knew he was going to pass it to Jim and then as soon as I saw how Jim was oriented, I knew that he was going to pass it to me... He usually plays to one player, often with a deviation so I got ready by moving up... There I hesitated to make a direct kick... I wanted to move up closer and after I moved off to the side..." (Flynn).

These units of activity were then subjected to in-depth investigation during the elicitation interview, which is a technique for questioning a subject (Vermersch, 1999, 2012). The technique is designed to guide a person in recalling a given experience by redirecting his attention to specific aspects of an experience so that he can then precisely describe it (Petitmengin, 2006; Vermersch, 2009; Valenzuela-Moguillansky, 2013). The elicitation interview has been used in cognitive (e.g., Lutz et al., 2002), clinical (e.g., Petitmengin et al., 2007), and sports (e.g., Villemain and Hauw, 2014; Gesbert and Durny, 2017) research. It is used to access detailed phenomenological reports of an individual's past experience (e.g., Varela and Shear, 1999; Depraz et al., 2003; Petitmengin et al., 2013; Olivares et al., 2015).

The process of carrying out an elicitation interview can be described as four main steps (e.g., Petitmengin, 2006; Vermersch, 2012): (a) the selection of a past experience, (b) the evocation of this experience, (c) the description of the diachronic dimension of the experience (i.e., the flow of experience that is the chaining of activity units), and (d) the deepening of the experiential aspects that characterize each unit of the activity (for an illustration, see Valenzuela-Moguillansky, 2013). In the present study, the first researcher selected the past experience. Indeed, it was important to have all the players involved in a given extracted offensive transition situation provide descriptions of their lived experiences.

Therefore, the first researcher prompted each player to describe his lived experience during the extracted offensive transition situation. To do so, he led the player toward an evocation of his own past experience as if he were reliving it. This was achieved by helping him to rediscover the spatio-temporal context of the experience (when, where, with whom?) until the past situation was more present than the interview situation and the player was relating to this past experience. For example, the interviewer sometimes used questions about the spatio-temporal context of the experience to which the player could not reply without referring to the past situation (e.g., When you're repositioning yourself in the team's defensive line, what are you concentrating on?; see Petitmengin, 2006, for further details). Last, the interviewer was sensitive during the elicitation interview to behavioral indicators (e.g., the use of the present tense, a slowing of the word flow, the shifting and unfocusing of the eyes...) that indicated how the player was relating to his past experience. Once he was in state of evocation, the interviewer used the physical and/or mental actions that the player had carried out throughout the specified situation as a guide for questioning (e.g., Petitmengin, 2006; Vermersch, 2009, 2012; Valenzuela-Moguillansky, 2013). After asking him about the temporal evolution of his actions (i.e., And then...what are you doing? What are you thinking about?) and the different stages of his experience, the interviewer guided him to direct attention to finer levels of the experience in each stage on the basis of five other experiential categories: objectives (i.e., What are you trying to do?), attention (i.e., What are you concentrating on?), expectations (i.e., What are you expecting?), projections (What are you expecting will happen?), and mobilized prior knowledge (i.e., What kind of situations do you feel you are in at this moment? Do you recognize the feeling in this situation? Is it new?).

The first researcher, who had been trained in elicitation interview techniques and had gained considerable experience, conducted a total of 22 interviews. These lasted 30–45 min, were video-recorded, and then were transcribed in their entirety.

Data Processing

The video recordings were reviewed to create an inventory of the players' movements during the unfolding situations. The verbalization data were processed in four steps: (a) reconstructing the diachronic and synchronic dynamics of the players' lived experiences (e.g., Gesbert and Durny, 2017), (b) synchronizing and connecting each players' units of activity (e.g., Bourbousson et al., 2015), (c) describing the regulation modes enacted by the players, and (d) comparing the occurrences of the collective regulation modes in relation to the moment in the situations.

Reconstructing Diachronic and Synchronic Dynamics of the Players' Lived Experiences

The first stage consisted of describing each of the players' lived experiences of the offensive transition situation. To do so, we used the *semiose* part of the psycho-phenomenological framework (Vermersch, 2012; Petitmengin, 2014) that corresponds to the players' sense-making process in situation (e.g., Varela et al., 1991; Di Paolo et al., 2010; McGann et al., 2013). First, from each player's descriptive statements we reconstructed the stream of his lived experience by identifying the succession of linkages between action and situation (i.e., unit of activity) considered at the level of what he enacted at the phenomenological level. These characterized the player's step-by-step experiences during offensive transition situation:

> "... Jim passes to me. I control the ball and then speed up toward the goal. I see that the goalie is advanced and I think about making a lob shot. Then I realize that I'm a little far and that I can move up closer. I speed up and then I feel an opponent behind me. I think to myself that at that speed, it's going to be kind of complicated to finish..." (Flynn).

Second, we characterized the synchronic dimension of each unit of activity. To do so, we used six experiential categories: the player's objectives during the phase of play (O), the motor or mental actions carried out by the player to achieve his objective (A), the sensorial attentional content that was significant at the player's level of perception (S.Att.c), the player's expectations about the possible actions that his opponents or teammates might make (E), the player's projections about integrating his action with a teammate's action (P), and the knowledge used or built during the player's action (K). The player's statements were thus gradually assigned to these different categories. The interactions between these different categories enabled us to coherently reconstruct the player's lived experience in its synchronic dimension. To facilitate the assignment of categories, we used the video recordings to create an inventory of each player's movements and provide us with an extrinsic description of the action taking place; during the interviews, we also insisted on the coherent organization of the collected category information (see **Table 1**).

TABLE 1 | Illustration of a player's unit of activity at a given moment of the situation.

Extrinsic description	Phenomenological contents
The left-back defender has the ball. He passes it to right-back defender.	(S.Att.c) The opponent player to my left has the ball—I'm a little in front of the half-way line (O) Be lined up with my teammates (E) Don't let anyone through (A) Look around at my teammates (S.Att.c) Arnold is on my left—Phil is pretty close—Jim is in front of me a little off to the side

A, action; O, objective; E, expectation; S.Att.c, sensorial attentional content.

These data were then used to identify the regulation modes enacted by the players. We particularly took into account the *objective*[1] category because the objective circumscribes a players'

[1]This notion of objective is assumed to be broad enough to deal with other concepts such goal (Schiavio and Høffding, 2015) or involvement (R'Kiouak et al., 2016).

activity in a given situation and thus provides access to the meaning the player is enacting at any instant.

Synchronizing and Connecting Each Player's Units of Activity

To describe and analyze how each player adjusted his activity with regard to his teammates (i.e., team coordination), we used a procedure for synchronizing the players' experiences (e.g., Bourbousson et al., 2015; R'Kiouak et al., 2016; Gesbert and Durny, 2017) and focused on the objective category. The players' units of activity were thus connected by presenting them side-by-side in chronological order (see **Table 2**).

This connection was made using an extrinsic description of the unfolding situation provided by the video recordings. Once the players' units of activity were step-by-step connected, each connection was viewed as a collective unit corresponding to which and how individual objectives were linked at a given moment (e.g., Bourbousson et al., 2015; Araújo and Bourbousson, 2016). Each time one player experienced a change in his activity—in this case, a change in the pursued objective—a new connection arose and a new collective unit was identified. Seventy-five collective units were identified throughout the eight offensive transition situations.

Description of the Regulation Modes Enacted by the Players

The third step was to characterize how each player experienced the adjustments made with respect to his teammates and opponents. The objective category circumscribes the players' activity by taking into account any instant meanings they are enacting. Each collective unit of activity was clustered using the related objectives within the three categories of regulation modes—local (L), global (G), and mixed (M). Local mode took into account how a player adjusted his activity based on information from the immediate environment (e.g., behaviors of nearby teammates/opponents) or on a more distant one-on-one play between a teammate and an opponent. Global mode took into account the adjustment of activity based on information about the collective organization of a part of the team (e.g., the line of midfielders). Mixed mode described the adjustment of activity based on the actions of a nearby teammate/opponent and a more distant teammate/opponent (Gesbert and Hauw, 2017). These collective units were matched to collective regulation modes that enabled us to account for the relationships between individual player's experiences across the unfolding situation (see **Table 3**).

Comparing the Occurrences of These Collective Regulation Modes in Relation to the Unfolding Time of the Offensive Transition Situations

The 75 collective regulation modes were then compared in order to identify typical patterns. This comparison was carried out based on the typical phases that were present in all the offensive transition situations with reference to the coaches' analysis (FIFA, 2010, 2014; UEFA, 2012). These indicators were as follows: putting pressure on the opponent ball carrier, recovering the ball, and passing through the opponent's midline and the end of the situation. **Table 4** describes the collective regulation modes for each situation and for each portion of the offensive transition situation (e.g., from the throw-in to putting pressure on the opponent ball carrier).

Data Reliability

Several measures were taken to ensure the validity of the data. The first two authors, each experienced at conducting qualitative research independently, coded 20% of the data transcripts independently to identify the unit of activity and the first author then coded the rest. Similarly, the first and third authors coded

TABLE 3 | Illustration of a collective regulation mode at a given instant of an unfolding situation.

Extrinsic description	Collective regulation mode		
	Flynn	Jim	Phil
The left-back defender has the ball. He passes it to right-back defender.	G (GLOBAL)	G (GLOBAL)	M (MIXED)

TABLE 2 | Illustration of a collective unit of activity at a given instant of an unfolding situation.

Extrinsic description	Phenomenological contents		
	Flynn	Jim	Phil
The left-back defender has the ball. He passes it to right-back defender.	(S.Att.c) The opponent player to my left has the ball—I'm a little in front of the half-way line **(O) Be lined up with my partners** (E) Don't let anyone through (A) Look around at my teammates (S.Att.c) Arnold is on my left—Phil is pretty close—Jim is in front of me a little off to the side	(S.Att.c) The left-back defender has the ball (A) I think that I shouldn't stay in front alone **(O) Return to the defensive block** (A) Move back to midfield (S.Att.c) In front of Phil and Flynn who form part of a line of 4 midfielders,	(S.Att.c) The left-back defender has the ball (A) Look to where my immediate opponent is (S.Att.c) He's pretty far from the action **(O) Back off from my direct opponent so the opponent ball carrier can make the pass** (S.Att.c) The ball carrier decides to get the ball out (E) He's going to move the game to the other end

A, action; O, objective; E, expectations; S.Att.c, sensorial attentional content. Noted in bold are team members' objectives at the given moment when the given participant is acting.

TABLE 4 | Number of collective regulation modes for each study situation and each period characterizing them.

Typical phases	Situations								Number of collective regulation modes/period
	S1	S2	S3	S4	S5	S6	S7	S8	
Throw-in—Put pressure on the opponent ball carrier	3	2	2	3	2	1	1	1	*15*
Put pressure on the opponent ball carrier—Recover the ball	2	2	3	2	1	3	3	2	*18*
Recover the ball—Push through the opponent's midline	2	2	1	1	1	2	2	3	*14*
Push through the opponent's midline—End the situation	7	3	7	4	1	4	1	1	*28*
Number of collective regulation modes/situation	14	9	13	10	5	10	7	7	*75*

50% of the units of activity in the collective regulation modes. By proceeding with this double coding, we were able to endure agreement rates of, respectively, 80 and 95%. A third coding session was conducted for each of these two coding parts to reach consensus for the disagreement.

RESULTS

A detailed analysis of the collective regulation modes enacted by the players during the offensive transition situations identified four typical patterns of collective regulation modes between teammates. These patterns were labeled as follows: (a) reorganization in play formation, (b) adaptation to actions of putting pressure on the ball carrier, (c) availability to get the ball out of the recovery zone, and (d) shoot for the goal.

Reorganization in Play Formation

The main collective regulation modes that the players enacted in the first part of the offensive transition situations were G.G.G. (46.6%) and G.G.M. (33.3%; see **Table 5**). At the beginning of these situations, the players were not in positions typical of this type of situation due to game circumstances. They thus attempted to reposition themselves in relation to their teammates, as illustrated by the following verbatim:

> "...The opponent goalie has the ball...I'm back in the block with the others..." (Jim).
>
> "... The goalie has the ball in his hands. I reform the block... I put myself with the right midfielders" (Arnold).

This activity of repositioning was based on an awareness of the positions of several of their teammates, which they described as a line of players (e.g., be lined up with the other teammates in the midfield) or a defensive block (e.g., back in the block). These adjustments were thus encoded within a global regulation mode.

In contrast, some of the players were in an appropriate position at the same time. They kept an eye on the opponent ball carrier in order to assess his possibilities to act, without, however, neglecting their proximal opponent that is, the one they had defensive responsibility for. The following verbatim illustrates this enaction:

> "... I'm in position with my teammates... My direct opponent in right next to me. I'm waiting to see how it's going to go for the opponent ball carrier. I don't think he can go forward in dribbling since there are so many players in front of him... He has the option of playing it long, but he's not used to that. He can maybe pass to the lateral right-back player because Arnold is a bit too much off to the side... but since he got the ball out cleanly enough, I'm leaning more toward an inside game with the defensive midfielder" (Flynn).

TABLE 5 | Collective regulation modes enacted by the players for the pattern *Reorganization in play formation.*

Collective regulation modes	G.G.G.	G.G.M.	G.M.M.
Number	7	5	3
Frequency	46.6%	33.3%	20.1%

G, mode of global regulation; M, mode of mixed regulation.

Their adjustments were encoded within a mixed regulation mode by combining several areas of local information (e.g., areas linked to the proximal opponent and the opponent ball carrier).

The last collective regulation mode identified was G.M.M. (20.1%). It was composed of two units of activity characterized by a mixed regulation mode.

Adaptation to Actions of Putting Pressure on the Ball Carrier

The main collective regulation modes that the players enacted between putting pressure on the opponent ball carrier and ball recovery were M.M.M. (33.3%) and M.M. (33.3%), as described in **Table 6**.

Once repositioned in the team's defensive configuration, the players all had specific positions on the field (i.e., the defensive block was in place, with short distances between players both across and down the field). While checking on the opponent ball carrier's possibilities to act (e.g., the opponent ball carrier cannot play with a specific teammate), they adjusted to his behaviors as well as to the behaviors of their direct opponents, as illustrated by the following verbatim:

> "The central defender takes the ball. I see the other opponent on my left, I don't think he'll be able to reach him. I especially look at the one in front of me, he's not too well-oriented. He's facing the ball carrier. I'm close enough, at a fair distance. I position myself so he passes to the opponent as far down as possible and the defender thinks he'll have time to give it to him... the midfielder is also going to think that he has the time to take the ball" (Alan).

TABLE 6 | Collective regulation modes enacted by the players for the pattern *Adaptation to actions of putting pressure on the ball carrier.*

Collective regulation modes	M.M.M.	M.M.	M.M.L.	M.L.
Number	6	6	4	2
Frequency	33.3%	33.3%	22.3%	11.1%

G, global regulation mode; M, mixed regulation mode; L, local regulation mode.

TABLE 7 | Collective regulation modes enacted by the players for the pattern *Availability to get the ball out of the recovery zone.*

Collective regulation modes	L.L.L	L.L	L.L.M
Number	4	5	3
Frequency	28.6 %	35.7%	35.7%

M, mixed regulation mode; L, local regulation mode.

Based on their positions on the field, the players tried to reduce and/or manipulate the opponent ball carrier's possibilities to act. For example, the player situated in the most forward position sought to prevent the opponent on the ball from passing to his teammate to his right. To do this, his activity was organized around two areas of local information.

Our results also indicated that the last collective regulation mode identified in six of the eight situations was characterized by a local regulation mode (M.M.L. or M.L.). This regulation mode was enacted by the player nearest to the opponent ball carrier, as illustrated by the following verbatim:

> "The central defender passes him the ball. It's good, I can go now. I go full charge at him. He gets the ball with no change in rhythm. I feel him as soft, not too confident. I'm careful not to be eliminated. When I'm right next to him, I try to slow up a little but not too much..." (Alan).

After progressively getting closer of the opponent ball carrier for a one-on-one, he adapts his activity to the ball carrier's behaviors to regain the ball or limit his range of possible actions.

Availability to Get the Ball Out of the Recovery Zone

The collective regulation modes enacted by the players after regaining the ball were mainly L.L.L. and L.L. (64.3%; see **Table 7**). After regaining ball possession, the new ball carrier attempted to quickly play forward and find a fast solution to get the ball out of the recovery zone and eliminate any nearby opponents. He thus adjusted his activity only in relation to local and proximal information. His teammates adjusted their activity in relation to him and their proximal opponent.

> "I have to find a solution and there I see Jim who's available up ahead" (Arnold, ball carrier).
>
> "I have to have a solution for Arnold and then I make a decision because my defender is starting to manage things far into the opponent's half" (Jim, ball carrier's teammate).

The third collective regulation mode enacted by the players was L.L.M. (35.7%). Due to his position on the field, the third player was out of the immediate visual field of his teammate on the ball. He was interested in information about the ball carrier and/or another teammate, as well as proximal opponents, thus describing an interest in several areas of local information (i.e., a mixed regulation mode).

> "I see Zack intercept the ball. At that moment, I back off because I see that Jim has come to the inside. He's coming to help out. As soon as Jim sees a teammate alone, particularly me I think, he likes to play with just that player to speed up the game. I back off so I can be there while still keeping an eye on the sideline with the opponent's defenders" (Flynn).

Shoot for the Goal

The collective regulation modes enacted by the players after moving the ball away from the recovery zone were mainly L.L.M. (53.6%), L.L.L. (14.3%), and L.L. (14.3%; see **Table 8**). The new ball carrier wanted to attack the opponents' goal as quickly as possible. His proximal teammate situated in his field of vision was therefore the best solution to move forward. The ball carrier and this teammate thus continued to organize their activity in relation to local information. They adjusted their behaviors mutually and in relation to their proximal opponent. The following verbatim extract illustrates these enactions:

> "I pass the ball and make sure it ends up with Arnold... and then I signal to get it back ..." (Zack).
>
> "Zack passes me the ball... as soon as he's done this, he starts running deep into the opponent's half between the two center players..." (Arnold).

In view of his position on the field (e.g., out of the immediate visual field or too far from his teammate on the ball), the third player instead tried to prepare his future call for the ball or to get into position to wait for the defensive phase, as illustrated by the following verbatim:

> "Zack (ball carrier) doesn't pass me the ball. I begin to call for it in front of me, where there's no one. I run toward the goal and I bring along a defender by passing in front of him, in fact ..." (Stuart).

To do this, he paid attention to his ball-carrying teammate and/or his other teammates, as well as other opponents present in the area where he wants to go, realizing that both are interesting areas of local information (i.e., mixed mode of regulation).

The third player was also able to continue trying to interact with the teammate on the ball. He thus only adjusted his behaviors using the L.L.L. collective regulation mode.

The players enacted two other collective regulation modes during the attack (L.M.M. and L.M.G.). These modes were characterized by the attacking ball carrier, who wanted to finalize the attack. He only adjusted to the proximal opponent's behaviors, with a local mode of regulation, as illustrated by the following verbatim:

TABLE 8 | Collective regulation modes enacted by the players for the pattern *Shoot for the goal.*

Collective regulation modes	L.L.M.	L.L.L.	L.L.	L.M.M.	L.M.G.
Number	15	4	4	2	3
Frequency	53.6%	14.3%	14.3%	7.1%	10.7%

G, global regulation mode; M, mixed regulation mode; L, local regulation mode.

> ".... Jim passes to me. I control the ball and then speed up toward the goal. I see that the goalkeeper is advanced and I think about a lob shot. Then I realize that I'm a little too far away and that I can move up closer. I speed up and then I feel an opponent behind me. I think to myself that at this speed, it's going to be kind of complicated to finish... I choose to get out..." (Flynn).

The ball carrier's teammates tried to either accompany him or position themselves in the block in anticipation of a future play.

> "There, I can see that Tom made a difference. I get closer to the goal but not at a real good pace, I'm kind of in the axis of the field. I'm supporting Tom's action. A defender gets closer to Tom, it's the one I had at the beginning..." (Stefen)
>
> "I'm now a little far away to call for the ball...I'd rather get into the defensive block in case we lose the ball" (Angel)

DISCUSSION

In this study, we describe how individual soccer players adjusted their activity to the need for team behavior (i.e., What was the constant focus in the adaptations actively made by the players?) by analyzing phenomenological data. These data were related to the players' lived experiences throughout multiple offensive transition situations. We were thus able to characterize the pattern of collective regulation modes enacted by the team in order to coordinate. These results are discussed in two parts. First, our results suggest that team coordination may be grasped as a fluctuating phenomenon that can be described through typical patterns of collective regulation modes. Second, our results point out that soccer team coordination is supported by several processes of regulation at the level of the players' local couplings. Among these regulation processes, we propose a new mode of interpersonal regulation.

Team Coordination as a Succession of Patterns of Collective Regulation Modes

Our results identified four patterns of collective regulation during the offensive transition situations. These patterns reflect the way the players adjusted their activity at the level of activity that was meaningful for them.

The first pattern describes the reorganization of the team at the beginning of the offensive transition. Due to the previous situation of ball possession, the team was disorganized at this instant. Some players were not in the positions they would normally be in to recover the ball. To reposition correctly, they intuitively adjusted their activity by aligning in a defensive block or a line of players that was re-forming (i.e., global regulation mode). These results suggest that the players' activity was directed toward a global mode of regulation that they were all bringing about (Bourbousson and Fortes-Bourbousson, 2016). To get into position from this initial phase of disorder and enact the global regulation mode, they were sensitive to information about the line of players or the defensive block. This mode can also be described as attractive because the players actively sought its emergence, which in return directly supported their adaptive activity.

This phase of team reorganization was prior to the more crucial activity of ball recovery. Once the team's defensive configuration was set up, our results indicated the emergence of a second regulation mode. According to their position on the field, the players sought to gather information about both the opponent ball carrier's possibilities for action and their immediate opponent in order to restrain (e.g., block a pass) or conversely encourage (e.g., let a pass occur) their opponent's activity. They were more tuned in to the opponent ball carrier's actions and those of their direct opponent because their respective activities were above all organized around putting pressure on the ball carrier. The modes of adjustment enacted by the players were therefore mixed. These results indicate that the players modulated their activity by spontaneous adjustments to contextual information that they were sensitive to rather than by referring to pre-established actions (Blickensderfer et al., 2010; Eccles and Tran Turner, 2014).

After ball recovery, a third team regulation pattern emerged. The new ball carrier's teammates promptly became available to help get the ball out of the recovery zone. They were thus more tuned in to information about the ball carrier's behavior, as well as that of opponents in this area of the field. Since the information they were sensitive to came from their proximal environment, the players enacted local regulation modes. Typically, these regulation modes match those identified by the ecological dynamics approach (Araújo and Davids, 2016; Passos et al., 2016), despite being related to individual lived experience. The players engaged in exploratory activity to look for and find satisfactory solutions in order to be available for their teammate's attack, while also facing dynamical environmental constraints (e.g., variations in interpersonal distance from teammates and/or opponents).

Once the ball was taken out of this area, the ball carrier and one of his teammates continued to mutually adjust by adopting local regulation modes for a quick attack on the opponent's goal. The modes were local because the transient information came from their proximal environment. The third player either adjusted to the current ball carrier's behavior and those of nearby opponents as he sought solutions via a local regulation mode or he chose to adjust to a future ball carrier's behavior and that of opponents in the area where he wanted to call for the ball via a mixed regulation mode. The behaviors of the ball carrier and his partner thus seemed to be particularly pertinent information for the players to reach their objective. Similar to the previous pattern, this mode of regulation recalls those identified in studies using the ecological dynamics approach (e.g., Passos et al., 2016).

These results highlight how soccer team members use several modes of regulation to achieve team coordination during dynamic tasks. Team coordination may therefore be described and explained as the succession of collective regulation modes. Our results describe how these modes are related to specific properties of the unfolding situation and the meanings collectively attributed to them, thereby providing a response to R'Kiouak et al. (2016), who raised questions about the parameters controlling how team members switch dynamically from one regulation process to another during an unfolding team action. Although earlier studies described a basketball team's coordination dynamics during an official match through a network analysis of the type: *who takes whom into account* (Bourbousson et al., 2010, 2015), the present study examined the adjustments enacted by soccer players in situation by adopting a phenomenological enactive analysis—that is, by gaining access to those elements that perturbed them and organized their sense-making activities.

Our results show that the players were aware of the specific regulation modes that were embedded in the game. In the situation of not possessing the ball, they showed that regulation modes chained in a relatively predictable manner: the first regulation mode referred to the players' repositioning into the team's defensive configuration (i.e., adopting a global regulation mode), which was in fact preparation for the more specific activity of recovering the ball (adopting a mixed regulation mode). The fluidity with which these regulation modes chained may reflect the habits built up through long years of training (see the next point of the discussion). Conversely, when they possessed the ball, these regulation modes chained in a less predictable way. A training challenge would thus be to develop players' capacities to switch from a global or mixed mode of regulation during the phase of non-possession to a local regulation mode after recovering the ball. This appears to be critical because the players do not know how the modes will chain. The difficulty is thus to make this transition as quickly as possible in order to maintain or even increase the imbalance provoked within the opposing team.

Insights into Regulation Processes on a Sports Team

Our results provide insights into the nature of regulation processes enacted by soccer team members during dynamic tasks.

First, they show how the team members played in a relatively intuitive way during the phases of no ball possession: each player pursued a specific objective depending on his location on the field (e.g., prevent the pass between the player on the ball and one of his teammates). To do so, they adjusted their activity to the actions of the opponent ball carrier and his proximal opponent. In support of the results of other studies in the sports sciences (Bourbousson et al., 2010; Millar et al., 2013; R'Kiouak et al., 2016), they raise questions about the assumption of the need for *mutual awareness* to achieve team coordination (e.g., Reimer et al., 2006; LeCouteur and Feo, 2011). Our findings indeed show that the players were so absorbed in what they were doing that they paid no attention to their teammates; interpersonal regulation processes were therefore not the focus of the adaptations actively made by the players in these instants: the focus was instead on the opponent ball carrier's actions. This result suggests the emergence of a new mode of regulation between team members to achieve team coordination: the *indirect* interpersonal regulation mode. We employ the word indirect because this mode was mediated by one or more opponents and not by teammates. Further, this notion is linked to the findings of a study of a joint musical performance: Schiavio and Høffding, 2015) showed that an awareness of co-players' subjective states was not required for a string quartet's performance; the first violinist, for example, was able to play without awareness of his co-players' mental states. The authors determined that it was the quality of the music perceived by the musicians that in great part explained the co-performance. In the present study, our results indicate that the soccer players were not aware of their teammates as they coordinated to collectively recover the ball: they adjusted to each other through the behavior of the opponent ball carrier. Future research should examine what occurs in other team sports in order to determine whether this interpersonal regulation mode is specific to soccer.

Second, our results indicated a switch in regulation modes enacted by the players after regaining the ball. The ball carrier and one of his teammates mutually adjusted their activity based on a co-regulation process, whereas a third player adapted his activity in a one-directional way toward the ball carrier or the other partner. Using the terminology of Di Paolo et al. (2010), this player coordinated *to* his teammate rather than *with* him (i.e., one-sided coordination). At this moment, the players experienced a relatively high degree of temporal pressure, which can be explained by the effort being made by the opponents to reduce the imbalance resulting from the loss of the ball. Their positions and orientations on the field also made them more or less visible to all teammates, supporting the observations in basketball by Bourbousson et al. (2010). The players were thus often involved in managing direct opponents, as well as the teammates they were interacting with or expected to interact with. Factors like temporal pressure, position, or player orientation in the field may also influence the possibilities offered to team members that favor the co-regulation of their activity. Although our results do not allow us to discuss the regulation modes enacted by all the team members, they nevertheless suggest that co-regulation processes do not involve all members (Bourbousson et al., 2010; Bourbousson and Fortes-Bourbousson, 2016). They also bring new elements of knowledge to explain why an entire sports team did not need co-regulation to perform.

For instance, in the phases of no ball possession, our results describe how the players intuitively modulated their activity in relation to the behaviors of the opponent ball carrier (i.e., with an indirect interpersonal regulation mode). They indicate how the players' experiences were altered when they perceived that the defensive block was in place, suggesting typical interactions like preventing the opponent on the ball from passing to one of his teammates or giving that opponent the opportunity to pass to a teammate in a specific area of the field. Through years of training and competition situations lived by the players and the repeated patterns of player/environment interaction, they may have developed a set of dispositions to act: prereflective, practical, and tacit knowledge about how to act at this specific moment (e.g., Varela et al., 1991; Legrand, 2007). These dispositions might then have implicitly influenced their experiences and, under favorable environmental circumstances (e.g., our defensive block is in position), would then be reenacted (e.g., Hughson and Inglis, 2002; Merritt, 2015).

In addition, through extensive shared practice (i.e., 18 months of training and competition together), the players also had experienced repeated interactions with their teammates. From these repeated patterns, a collective prereflective knowledge about how to collectively regain the ball might have developed as a collective body memory (Fuchs, 2017). This memory can be defined as a set of the dispositions that characterize the members of a team, that have developed over the course of shared experiences, and that preordain the interactions between team members at a given instant (Fuchs and De Jaegher, 2009; Fuchs, 2016, 2017). These past and shared experiences (i.e., a collective body memory) are not represented throughout action; instead they are played out, actualized and reenacted in the course of the action being performed. Our results indeed describe how the players intuitively acted at these moments without the need to remember, without the need to explicitly recollect through representations what needed to be done for the team, without even taking into account other teammates. Accustomed to these game phases, the players had acquired and embedded throughout their past experiences of training and competition a set of dispositions to act that they used in a prereflective way in connection with the possibilities that were emerging from the environment. We suspect that the development of this collective body memory may be a plausible explanation of why team members do not need to co-regulate their activity in order to coordinate.

Future research should investigate the effect of training on the enaction of this type of interpersonal regulation between team members in competition. Due to the lability of high-level soccer teams (e.g., Gourcuff, 2009), we think this type of research would be relevant to shed light on the effects of training settings for the development of collective body memory.

AUTHOR CONTRIBUTIONS

VG, AD, and DH collected and processed data. VG and DH co-wrote the manuscript.

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Understanding and Modeling Teams As Dynamical Systems

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By its very nature, much of teamwork is distributed across, and not stored within, interdependent people working toward a common goal. In this light, we advocate a systems perspective on teamwork that is based on general coordination principles that are not limited to cognitive, motor, and physiological levels of explanation within the individual. In this article, we present a framework for understanding and modeling teams as dynamical systems and review our empirical findings on teams as dynamical systems. We proceed by (a) considering the question of why study teams as dynamical systems, (b) considering the meaning of dynamical systems concepts (attractors; perturbation; synchronization; fractals) in the context of teams, (c) describe empirical studies of team coordination dynamics at the perceptual-motor, cognitive-behavioral, and cognitive-neurophysiological levels of analysis, and (d) consider the theoretical and practical implications of this approach, including new kinds of explanations of human performance and real-time analysis and performance modeling. Throughout our discussion of the topics we consider how to describe teamwork using equations and/or modeling techniques that describe the dynamics. Finally, we consider what dynamical equations and models do and do not tell us about human performance in teams and suggest future research directions in this area.

Keywords: teams, team cognition, interpersonal coordination, non-linear dynamics, communication analysis, teamwork

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WHY STUDY TEAMS AS DYNAMICAL SYSTEMS?

A team consists of two or more people that work interdependently toward a common goal (Salas et al., 1992). Counter to many approaches in psychology, understanding teams involves not just understanding isolated mental and behavioral processes in the individual but demands theories and models for how interacting with other people shape thought and behavior in real time. We argue that many approaches aimed at studying interpersonal dynamics, such as social psychology, tend to locate explanations of psychological phenomena within the individual, rather than actual interactions, which is a shift that team psychology demands (Cooke et al., 2013). Because so much of the human condition is based on interacting with other people, we argue that a shift toward interaction- and systems-based psychology, which working with teams entails, touches on a foundational issue in psychological science. For example, a central question when working with teams is, “How do real-time interpersonal processes change the way a person thinks and behaves?” In this article, we advocate a dynamical systems approach for answering this type of question. In this light, teams are viewed as a system of coupled elements that interact over time to produce patterns that are themselves not contained within the team’s members. In order to present a framework for understanding teams as dynamical systems, we first examine the concept of a system and what it means for team psychology.

To appreciate what a dynamical system is, we should first examine the concept of a system (Turvey, 2009). Whereas a system exists independently of whether or not it is recognized as a system (i.e., when something is part of a system, it behaves differently than if it were not a part of that system), *systems thinking* is a matter of perspective. For an astronomer, for example, we suppose the galaxy is a system, and the earth is an element of the system; for a climatologist, the earth is a system, and the earth's atmosphere is an element of the system etc. In other words, systems (and subsystems) can have fuzzy boundaries, but the important point is that when we use the word "system," we invoke explanations and understanding precisely at the system-level, rather than the constituent elements of the system (Chapanis, 1996). For example, by focusing on individual-level properties that exist outside of the team in action, "aggregate" views of team cognition that focus on alignment and complementarity of team member knowledge (see DeChurch and Mesmer-Magnus, 2010, for a discussion) present a non-system explanation of team cognition, whereas by focusing on interactions, more "holistic" approaches that view team cognition as the cognition that happens *while* team members interact (Cooke et al., 2013) present more of a systems explanation of team cognition.

At its most basic, the concept of a *dynamical* system (Abraham and Shaw, 1992) simply introduces a temporal element for understanding system behavior. In psychological terms, "dynamical" denotes an emphasis on process (in addition to structure) in understanding and modeling psychological phenomena (Thelen and Smith, 1994). The emphasis on process is important, because when elements are dynamically linked in a system, the ways in which those elements act are different than when those links are absent (Morgan, 2010). Put differently, behaviors can *emerge* at the system level that are not encoded at the level of isolated elements. This concept is captured in Kozlowski and Klein's (2000) distinction between compositional and compilational emergence in team cognition. Compositional emergence means that properties at the team level (e.g., team knowledge) are isomorphic to properties at the individual level (e.g., sum of individual knowledge). Compilational emergence means that properties at the team level are non-isomorphic to properties at the individual level, where team properties only emerge through the process of team interaction (DeChurch and Mesmer-Magnus, 2010). We take the latter compilational form of emergence as a more general view of how teams work, wherein team interactions dynamically shape team members' thoughts and behaviors in ways that cannot be known *a priori*.

The fundamental psychological question we started with was how interpersonal processes shape human thought and behavior. Teams are ideal for addressing this question, and dynamical systems provide a powerful theoretical framework for understanding how mental and behavioral processes in the individual are shaped through teamwork. We study teams as dynamical systems because it allows us to directly address the question of how the system shapes element behavior in order to make predictions about future states of the system and the elements in it. By the end of this article, we hope to demonstrate three general principles based on this approach:

(1) Local variability ensures global stability, and global stability entails local variability: Although team interactions can be highly variable and unpredictable on small ("local") timescales, they are necessarily so in order to maintain stability and predictability of the team on larger ("global") timescales.
(2) From heart rate variability (Peng et al., 1995) to postural control (Collins and De Luca, 1995), local variability with global stability is a principle that characterizes processes operating at different levels of analysis. Similarly, local-global dynamics in teams are substrate-independent and occur across perceptual-motor, cognitive-behavioral, and neural levels of analysis.
(3) Extending Principles 1 and 2, "cross-level" effects occur between levels of analysis, such that we can gain insight into dynamic processes on one level of analysis (e.g., cognitive-behavioral) by engaging and/or observing the dynamics at another level of analysis (e.g., neural).

We begin by explicating several concepts that will aid in understanding how a dynamical systems approach has been applied to teams.

DYNAMICAL SYSTEMS CONCEPTS IN THE CONTEXT OF TEAMS

Having introduced the general notion of dynamical systems, in this section we describe several concepts of dynamical systems that we have found useful for the study of teams. We describe attractors, perturbation, synchronization, and fractal (power-law) concepts and how they relate to the study of teams.

Attractors

An attractor is a behavior that a system settles on over time after (possibly) displaying initial transient (settling-in) behavior (Abraham and Shaw, 1992). In predicting system behavior, the system will gravitate toward the attractor, regardless of where it "starts out at" or is "pushed to" by an outside force (e.g., a perturbation; see below). Some attractors are inherently *stable*, such that if the system is pushed away from the attractor it quickly returns to the attractor. Some attractors are *unstable*, such that if the system is pushed away from the attractor, it will be hard to return to the attractor. Other attractors are *metastable*, such that stability must be maintained through active control (a teamwork example is provided later). Sometimes the attractor is cyclical and forms oscillations. For example, pendulum clocks have an oscillatory attractor. In teams, attractors and their stability have been researched in motor coordination and communication processes (described later), where the formation of behavioral attractors for adapting to changing environmental demands has been a central issue (Gorman et al., 2010a,b; Gorman and Crites, 2015).

Perturbation

A perturbation is an outside disturbance to a system that forces either a reorganization of the behavioral trajectory toward an attractor or moves the system toward a new attractor (Abraham and Shaw, 1992). The effect of a perturbation on the system depends on the system's stability. A perturbation to a highly stable system is unlikely to shift the system's behavior to a new attractor. Conversely, a system that is attempting to reach an attractor state during the initial transient period will be highly impacted by a perturbation because system behavior is not stably tied to an attractor. In this respect, the system's response to a perturbation can be used either as an index of attractor stability (its "relaxation time") or to "push" the system around its coordination space in order to influence attractor development (Schöllhorn et al., 2006; Frank et al., 2007; Gorman et al., 2010b). In teams, perturbations and stability have been researched in the context of team longevity and training to develop adaptive teams that respond effectively to novel task demands and events in the environment (Gorman et al., 2010a,b).

Synchronization

Synchronization is a phenomenon where two or more coupled oscillatory processes become coordinated in time across some proportion of frequency (e.g., 1:1, 2:1; Strogatz, 2004). *Coupling* simply means that the processes have some form of interaction with each other. For example, if two pendulum clocks having oscillatory attractors are coupled by placing them on the same surface, the pendulums couple through the surface and eventually oscillate together in time (i.e., synchronize). The synchronization that is observed over time is a new attractor that may not correspond to the natural frequencies of the uncoupled oscillators. Synchronization is an important concept for teams because it describes the impact team members have on each other when they are *informationally* coupled (e.g., through perceptual channels; through communication). Moreover, there are different types of synchronization that can occur (e.g., different frequency proportions, 1:1; 3:2; 7:5; etc.) between team-member inputs. Synchronization can occur during interpersonal coordination both unintentionally and intentionally (Richardson et al., 2005, 2007; Varlet and Richardson, 2015). In teams, synchronization has been researched in communication and team neurophysiology (Stevens and Galloway, 2014, 2016; Gorman et al., 2016), physiological synchronization (Guastello, 2016; Guastello et al., 2016), and in perceptual-motor synchronization (Gorman et al., 2017).

Fractals and Power Laws

Fractals (Mandelbrot, 1967) model either spatial or temporal processes in which similar patterns occur across multiple scales (e.g., timescales) of measurement. To say that a system exhibits temporal fractal structure, for example, means that it displays a temporal nesting property such that smaller copies of a pattern are nested within larger copies of the pattern, a property called scale-invariance. Scale-invariant processes are fit by a power-law distribution (Schroeder, 2009). Power laws are a signature of self-organization (Bak, 1996) and long-memory effects (Beran, 1994). Self-organization is a process wherein order at the global scale emerges from and constrains component behavior at the local scale (Kelso, 1995), and long-memory effects are correlations that persist over longer timescales than those that characterize local variability within the system (Beran, 1994). When those correlations are positive, it is called *persistence*, and when they are negative, it is called *antipersistence*. It should be noted that system behavior can self-organize around other attractor states (e.g., fixed point; oscillatory); however, we will focus on how teams self-organize around metastable and critical states that exhibit fractal and long-memory dynamics. In psychology, power laws capture fractal scaling in cognitive processes (Gilden et al., 1995; Van Orden et al., 2003) and learning curves across groups of learners (Newell et al., 2001). Fractal scaling has been observed in interpersonal tasks when people match complex movement and communication patterns (complexity matching) that vary across local and global scales (Marmelat and Deligniéres, 2012; Abney et al., 2014; Fine et al., 2015; Coey et al., 2016). In teams, power laws have also been researched in the formation of long-memory in team communication (Gorman, 2005) and in team perceptual-motor learning (Gorman and Crites, 2015), whose timescales extend beyond the memory limitations of the individual. In accordance with Principle 1, fractals and power laws distill what is lawful at the global scale from what appears to be "messy" or "noisy" at the local scale.

TEAM DYNAMICS ACROSS LEVELS OF ANALYSIS

Just as there are different *scales* of analysis (i.e., local vs. global; short timescale vs. long timescale), there are also different *levels* of analysis, including perceptual-motor, cognitive-behavioral, and neural. From a systems perspective, just as processes are temporally linked across scales of analysis, they are physically and informationally coupled across levels of analysis. Therefore, a challenge from the systems perspective is to learn how team dynamics are reflected across different levels of analysis. For example, how are more overt processes observed at the perceptual-motor and cognitive-behavioral levels (e.g., action; communication) coupled with more covert physiological processes at the neural level? In the remainder of this section we present research that examines the unifying dynamical principles outlined above (Principles 1–3) across perceptual-motor interpersonal dynamics, cognitive-behavioral communication patterns in teams, and neural synchronization as a function of team communication patterns ("cross-level" effects). In these sections we also present unifying concepts that get at the question of how team processes shape team members' thoughts and actions in the form of unintentional synchronization, self-organization, and long-memory effects.

Team Dynamics at the Level of Perceptual-Motor Coupling

This section describes research on interpersonal synchronization, where behavioral attractors for interpersonal coordination include 1:1 synchronization and more complex (e.g., 3:1) forms of synchronization. The results described in this section begin to demonstrate how team dynamics structure individual behavior. Moreover, in this section we begin to illustrate how the general dynamical principle that teams perform more variable patterns on local scales that contribute to coherence and consistency on a global scale (Principle 1) is realized at the perceptual-motor level of analysis.

One demonstration of perceptual-motor coupling is based on an interpersonal synchronization phenomenon reported in a large number of studies (e.g., Schmidt et al., 1990; Amazeen et al., 1995; Richardson et al., 2007; Ouiller et al., 2008; Gipson et al., 2016). In one version (Ouiller et al., 2008; Gipson et al., 2016) the demonstration involves two people sitting and facing each other while performing oscillatory finger movements (i.e., oscillating the index finger up and down in the vertical direction; **Figure 1A**). From these finger oscillations, we measure the relative phase (Kelso, 1995; the difference in the phase angles of each person's finger oscillations; **Figure 1B**) and peak frequencies of their movements (**Figure 1C**). Critically, they cannot always see each other. Visual coupling (being able to see each other's movements) is used to induce the spontaneous interpersonal dynamics effect. As shown in **Figure 1A**, visual coupling is controlled using visual occlusion goggles. Participants' instructions are to oscillate their right index finger at a comfortable pace when they hear a start beep. For the first third of the trial, the goggles are occluded (no visual coupling). Notice in the power spectrum in **Figure 1C** the gray and white curves have different peak frequencies during the first third of the trial, which corresponds to the comfortable oscillation speed of each participant with goggles occluded. The only other instruction participants receive is "when you can see, look at the other person." During the second third of the trial, the goggles are un-occluded, and they can see each other. This visual coupling is accompanied by spontaneous 1:1 synchronization, represented by a shift in relative phase toward zero (**Figure 1B**) and a spontaneous overlap in their peak frequencies (**Figure 1C**) during the middle third of the trial. That is, with no guidance, dyads unintentionally drift toward a state of 1:1 synchronization, the natural attractor of the system. What is revealing is that it is not at a movement frequency that either participant naturally prefers; it is a new behavior that emerges out of interpersonal interaction. Related to the question we started with in the section "Why Study Teams as Dynamical Systems?" this is an example of how interpersonal interaction can change a person's behavior in unexpected ways. The last third of the trial shows how participants' movements drift apart when the goggles are once again occluded (no visual coupling). However, we have found that the drift is not instantaneous; there is a "social memory" effect (Ouiller et al., 2008; Gipson et al., 2016). That is, when the goggles are once again occluded, there is a carryover of the interpersonal dynamic to subsequent participant behavior.

This phenomenon might be related to mirroring or mimicry (Chartrand and Bargh, 1999). Mirroring is a phenomenon where if you are sitting across from someone and that person folds their arms, then this "activates" something in you, and you unconsciously fold your arms. Mirroring has been argued to be a pervasive phenomenon that is fundamental to all human interaction (Ramachandran, 2000; Rizzolatti et al., 2001). However, we will argue that 1:1 mirroring is but one of an infinite set of interpersonal ratios whose performance can be better predicted by dynamical systems, and from a team psychology standpoint, mirroring may actually be maladaptive. In team settings that require people to coordinate different but contemporaneous behaviors, spontaneous 1:1 synchronization—mirroring—is a tendency that must be overcome. This includes tasks requiring team coordination across more than one set of hands (e.g., robotic and laparoscopic assisted surgery; Bermas et al., 2004; Zheng et al., 2007; Guru et al., 2012; Liu et al., 2014).

Gorman and Crites (2015) described how mirroring might negatively impact performance in highly skilled tasks such as surgical knot-tying. The experiment did not use surgeons experienced at knot-tying but participants who were highly skilled in terms of tying their shoes; hence, shoe-tying was a model task for the surgical domain (**Figure 2**). When participants tied individually, their performance curves (trial times for tying a secure knot) were flat, indicating no room for improvement. In terms of individual knot-tying performance, they were experts, limited only by the biomechanical constraints of the task. However, when these experts were asked to work together as a team to tie the knot, there was still a lot to be learned, and their performance demonstrated a learning curve that approached individual performance only after 20 trials. Calculating a measure of between-hand synchronization, the authors found that skilled individual tying is characterized by contemporaneous but independent movements resulting in less synchronization between the hands compared to team tying, and amount of synchronization was positively correlated with trial time (i.e., more synchronization was linked to poorer performance). The authors concluded that when tying as a team, the spontaneous mirroring tendency takes over, and the hands spontaneously synchronize, and participants' hands are no longer able to move independently, which is what teams apparently need to learn to perform the task effectively. As demonstrated earlier with visually coupled dyads (**Figure 1**), 1:1 synchronization is the natural attractor of the system, which is why non-1:1 synchronization may be so difficult to achieve in a novel team context. We think that the interpersonal skill needed for the novel team tying task may be similar to the skill individuals acquire when learning to play a piano or guitar, where an early challenge is to get their hands to move contemporaneously but independently to produce the desired musical notes (Furuya and Kinoshita, 2008; Furuya and Soechting, 2012).

Mirroring is thought to be a pervasive interpersonal dynamic, perhaps rooted in our nervous system (Rizzolatti et al., 2001), but many tasks, such as dancing, playing sports, and coordinating manual labor require that people *not* mirror. Because interpersonal activities are coordinated across and not just within physiological and motor systems, models that are not limited to within-person explanations (e.g., mirroring) are needed. Frequency-locking dynamics provides a model that describes the stability of not just 1:1 mirroring but an infinite range of frequency ratios (e.g., 3:2, which is a more complex, non-mirroring pattern). A graphical depiction of the model

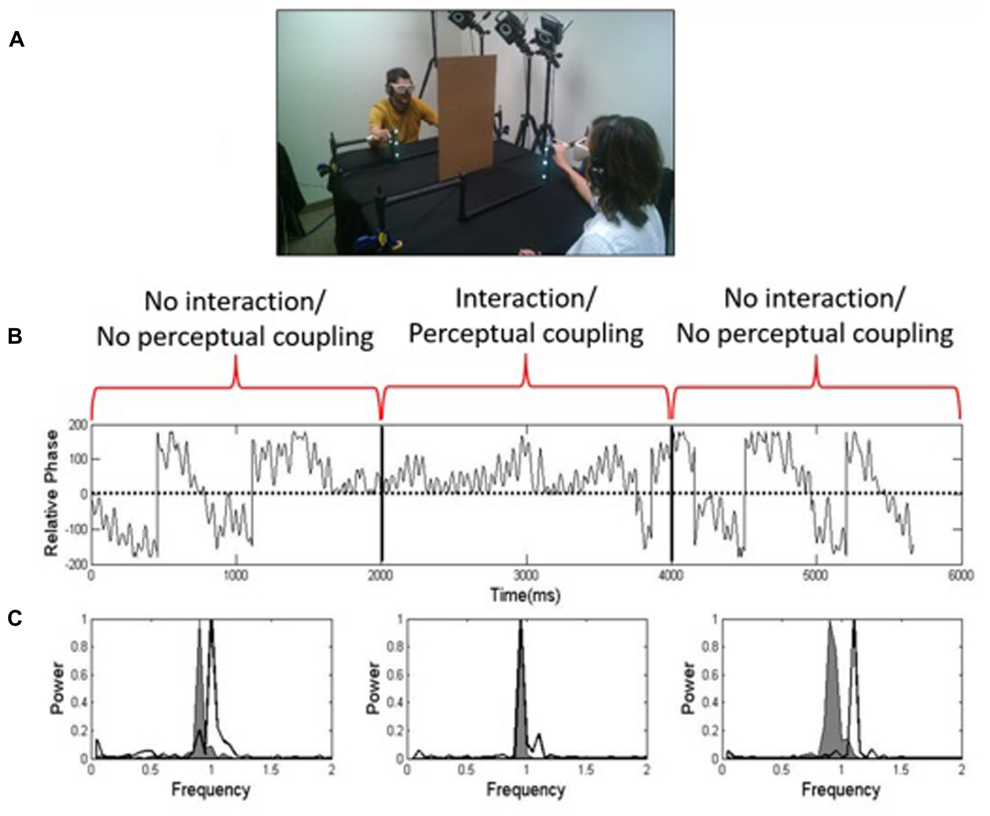

FIGURE 1 | (A) A task demonstrating how perceptual coupling and interpersonal interaction induces spontaneous synchronization between people; **(B)** relative phase of participants' finger oscillations over a one-minute trial; **(C)** power spectra indicating the peak frequencies of participants' finger movements when vision is occluded (left), un-occluded (middle), and once again occluded (right) (from Gipson et al., 2016; reprinted with permission).

for coupled oscillators (e.g., coordinating interpersonal finger oscillations), called the Arnold tongues, is shown in **Figure 3** (Treffner and Turvey, 1993; Peper et al., 1995). For every ratio on the horizontal axis, there is a black Arnold tongue, whose width indicates the stability of the attractor for that ratio. There are an infinite number of Arnold tongues in the interval [0, 1] (i.e., for any ratio), but most ratios are too unstable for people to perform—the skinnier the tongue, the harder it is to keep the ratio. Moving vertically up and down any tongue, it gets wider or narrower, which is a function of the coupling strength between oscillators. Coupling strength can be operationalized as amount of perceptual (e.g., visual; auditory) information exchange between people. Hence the model predicts that while mirroring (1:1 synchronization) is most stable, performance of some non-mirroring patterns (e.g., 2:1) will be more accurate and stable than others (e.g., 4:1) and that increases in coupling strength make the performance of any ratio more accurate and stable.

Our results using the interpersonal finger oscillation task (e.g., **Figure 1A**) align with these model predictions, but with interesting twists based on inherent properties of the human visual system (Gorman et al., 2017). **Figure 4A** shows accuracy of five simple ratios, one of which (1:1) corresponds to perfect

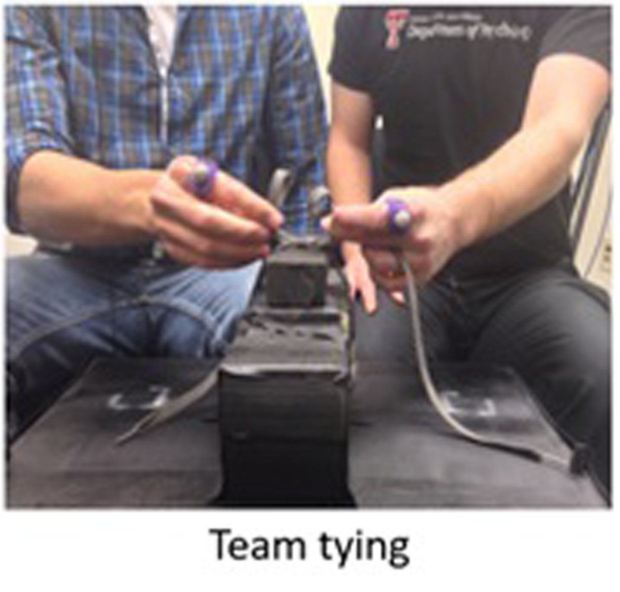

FIGURE 2 | In the team tying task each person handles one lace using one hand but otherwise attempts to tie a shoelace as they normally would.

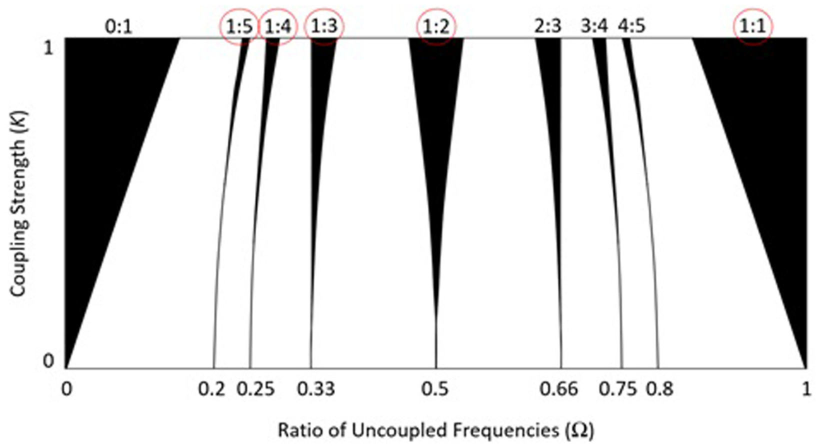

FIGURE 3 | The black Arnold tongues represent the periodic behavior of coupled oscillators in an iterated circle map ($\theta_{n+1} = \theta_n + \Omega - K/2\pi \times \sin[2\pi\theta_n]$; θ = phase of oscillation). The width of the Arnold tongues corresponds to predicted stability of frequency ratios as a function of the intended ratio (Ω) and coupling strength (*K*) between coupled oscillators (performance of the circled ratios is described in the text) (from Gorman et al., 2017; reprinted with permission).

1:1 mirroring. As the intended ratio moves farther from perfect mirroring, corresponding to narrower tongue widths, performance becomes less accurate. This is not surprising: the more different the movements, the harder they are for people to keep. However, more support for model predictions can be seen in **Figure 4B**, which shows the effect of % visual occlusion (coupling strength) on the stability of any ratio (more error implies less stability). As shown on the right side of **Figure 4B** (1,000 ms), in accordance with model predictions the higher the visual coupling the more stable any ratio. However, it is important to note how the properties of the human visual system can modify these dynamics (the need to account for individual-level properties in the context of team dynamics is addressed in the later section Criticism of the Dynamical Systems Approach and Future Directions). The 60 ms rate in **Figure 4B** is below the critical visual fusion rate (Card et al., 1983), which corresponds to the principle behind motion pictures that if discrete images are put together fast enough, then people will perceive them as a continuous visual stream (Hochberg, 1986). If people are provided with deprived or noisy information *under* the critical fusion rate (e.g., the 60 ms rate), then they tend to fill in the missing coordinative information to preserve interpersonal performance even for more complex, non-mirroring patterns. Based on this, mirroring alone may not explain interpersonal coordination as well as previously thought, or why our perceptual systems fill in more complex, non-mirroring patterns when we coordinate with each other. Systems-level explanations, such as frequency locking, provide additional insight into how people coordinate not only mirroring but also non-mirroring behaviors with each other.

An example of actual team performance that aligns with what we observe in the laboratory can be found in the sport of Double Dutch (Gorman et al., 2017). Double Dutch is a team sport involving two people on either end of two long jump ropes who simultaneously twirl both ropes while another person jumps over the twirling ropes. Working with the National Double Dutch League, we have investigated non-mirroring coordination patterns between rope turners' and jumper's movements under the predictions of frequency-locking.

Figure 5A shows a highly skilled team performing a 7:5 footfall-to-rope-turn ratio. Their performance is incredibly consistent (**Figure 5B**), given the predicted difficulty of the ratio. Compared to a 1:1 ratio (mirroring), which even beginners can perform, as they move further from mirroring, they increase their coupling strength through increased visual attention and through rhythmic counting, which is a more cognitive form of coupling. In terms of the model, by increasing coupling strength, they effectively widen any tongue, which allows them to stabilize any ratio.

When performing this complicated pattern, participants modify the 7:5 pattern cycle-by-cycle. That is, for one 7:5 grouping of movements, they perform a particular pattern, and for the next 7:5 grouping of movements, they perform a different pattern, such that the pattern is locally variable but globally stable. As shown in **Figure 6**, the way the red footfalls are interspersed with the blue rope turns varies on a local (cycle-by-cycle) scale but is stable on a global (overall pattern) scale. This recounts the idea that teams perform more variable patterns on local scales that contribute to coherence and consistency on a global scale (Principle 1), which, as discussed next, appears to be something that is fundamental to team performance across levels of analysis (Principle 2).

Team Dynamics at the Level of Cognitive-Behavioral Coupling

This section extends Principle 1 to the cognitive-behavioral level of analysis, demonstrating how local-global dynamics occur across different levels of analysis in teams (Principle 2). We focus on how individual communication and coordination behaviors are dynamically structured to maintain team effectiveness at the global scale. Moreover, we demonstrate how team dynamics at the cognitive-behavioral level compel team members to

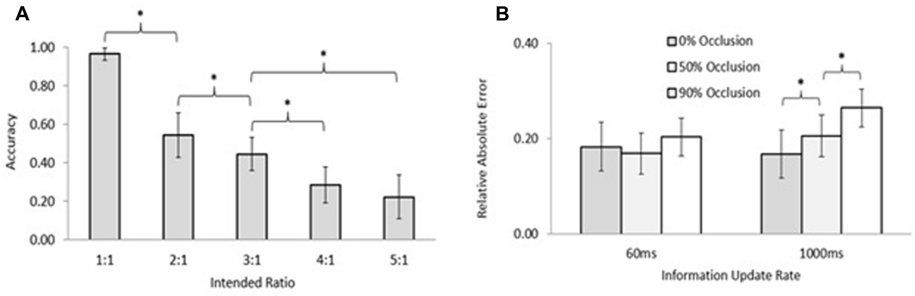

FIGURE 4 | (A) Accuracy of interpersonal coordination of mirroring (1:1) and non-mirroring (2:1–5:1) patterns aligns with Arnold tongue predictions; **(B)** visual occlusion (lower coupling strength) makes any ratio less stable (more error) above the critical fusion rate (1,000 ms update rate); however, humans tend to fill in missing information for any ratio when the presentation rate is below the critical fusion rate (60 ms) (from Gorman et al., 2017; reprinted with permission).

communicate in somewhat unpredictable ways at a local scale that nevertheless contribute to coherence and consistency—here, fractal and power law dynamics—on a global scale.

Another useful model for team dynamics is the inverted pendulum. If this is not familiar, think of trying to balance a rod upright in your hand (**Figure 7A**). The challenge is to maintain the upright balance although the rod's natural tendency—its natural attractor—is to fall to the ground. The rod balanced upright is a metastable state that is created when your hand movements counteract the natural tendency of the rod to fall to the ground (Treffner and Kelso, 1999). The hand movements may appear random or unpredictable, but this behavior is necessary for keeping the overall system (i.e., rod balanced upright) stable and predictable on a global scale. Similarly, although team members share a common goal, because they operate in dynamic environments the natural tendency of team members is to behave in ways that might seem unpredictable on a local scale but necessarily so in order to maintain team effectiveness on a global scale (Gorman et al., 2010a). In this regard, team dynamics contains a metastable state that is maintained through team interaction at the cognitive-behavioral level of analysis (e.g., team communication).

Interactions among three-person uninhabited air vehicle (UAV) teams—a photographer, pilot, and navigator working together to take ground photos—demonstrate these dynamics (Gorman et al., 2010a). We used timestamps of critical team coordination events needed for taking photos of ground targets and combined these into a coordination score (**Figure 7B**). The coordination score captures the temporal relations of the critical coordination events for each ground target and exhibits inverted pendulum dynamics (**Figure 7C**). On short timescales we see persistence, and on longer timescales we see antipersistence. In the inverted pendulum, drifts away from straight up in a particular direction (persistence) occur on short timescales, and these drifts are counteracted by corrections back to straight up (antipersistence) on longer timescales. Similarly in the UAV teams, short timescale (local) variability in terms of a particular target coordination pattern is bounded by a longer timescale (global) coordination pattern across all targets (Gorman et al., 2010a). Again, this is the theme of more variable patterns on local scales that contribute to coherence and consistency on a global scale (Marmelat and Deligniéres, 2012; Principle 1).

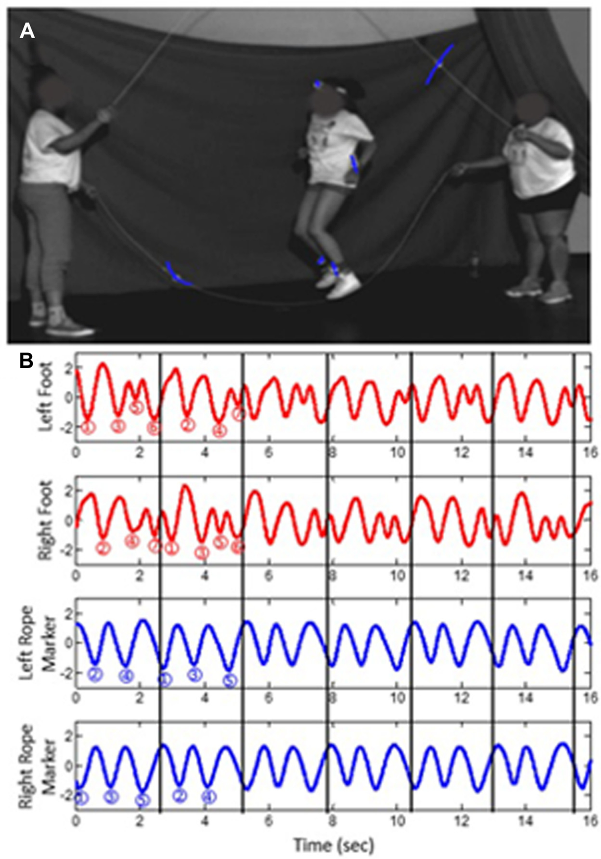

FIGURE 5 | (A) A highly skilled Double Dutch team at the National Double Dutch League summer camp; **(B)** performance of a 7:5 (foot:rope) ratio by the team (from Gorman et al., 2017; reprinted with permission).

This principle is also apparent in the temporal nesting of communication behavior over time. **Figure 8** shows a sequence of communication codes obtained from transcribing a team's conversation, separating it into utterances, and coding

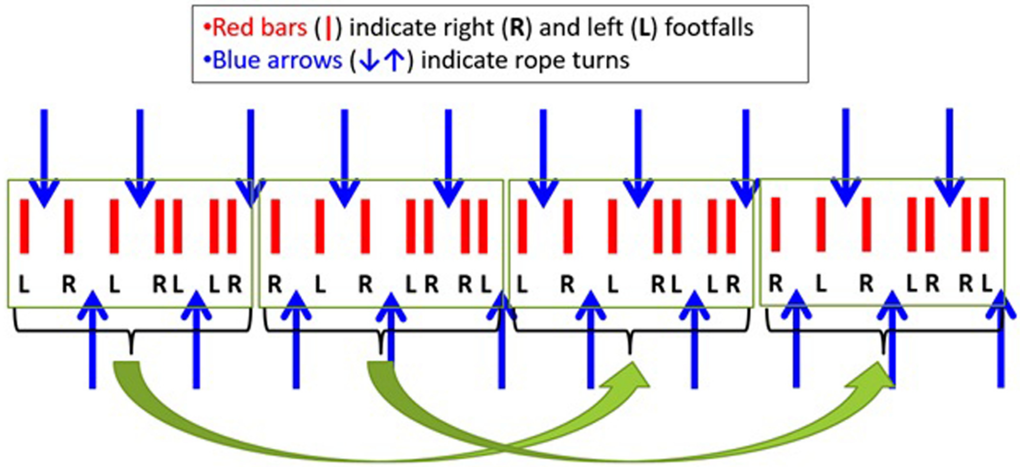

FIGURE 6 | To maintain a stable ratio on a global (overall pattern) scale, teams can vary their patterns on a local (cycle-by-cycle) scale.

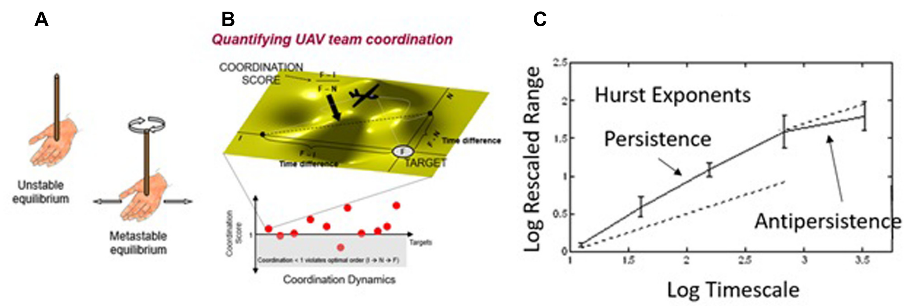

FIGURE 7 | (A) The inverted pendulum; **(B)** UAV team coordination score; **(C)** short-range persistence and long-range antipersistence of the coordination score follows inverted pendulum dynamics.

them using a mutually exclusive set of communication types, comprised of Solicitation, Sharing, Iteration, and Consensus (Gorman et al., 2009). Looking at the code sequence over time, it appears random, perhaps resembling a memoryless Poisson process. In that case, a Markov model (**Figure 8B**) can account for local variation in the sequence of codes (i.e., which code tends to follow which), as indicated by the smaller ovals in **Figure 8C**. But, there is a good amount of unexplained variation using this approach (Gorman et al., 2009), leading one to wonder how accurately a Markov model describes the process that generated the sequence of codes.

As we incorporate longer timescales, we see that the conversation continues to exhibit the transition structure of **Figure 8B**, but operating on a longer timescale (i.e., the larger oval, "Vehicles," in **Figure 8C**), suggesting a temporal fractal structure for team communication. For example, on short timescales you might find these code transitions in a discussion of airplanes and boats, but those short timescale conversation transitions are nested within a longer timescale conversation about vehicles in general. Hence, though linear transition models such as Markov models do account for some local variation during conversation, we must also account for non-linear (fractal) nesting of conversation topics across longer timescales. More recently, we have quantified this process in action-based teams who coordinate across real-time perception-action links and decision-making teams who coordinate across more cognitive, planning links (for a discussion of these team types, see DeChurch and Mesmer-Magnus, 2010).

Dunbar and Gorman (2014) examined the impact of task constraints on the temporal fractal structure of team communication. In this study, dyads performed either an action-based task or a decision-making task selected to introduce different team interaction constraints. After teams performed their task, their communication was transcribed and coded using Butner et al.'s (2008) coding scheme into three mutually exclusive code types: Facts (i.e., communication focused on perception and action), Interpretations (i.e., communication focused on cognitive processing), and Conversation Regulation (i.e., communication focused on maintaining the flow of conversation). The temporal distribution of each code was evaluated for each team's transcript and converted into slopes of the line relating log scale size (possible number of intervening codes between each occurrence of the code [e.g., Fact] being analyzed) by log frequency (frequency count of the number of

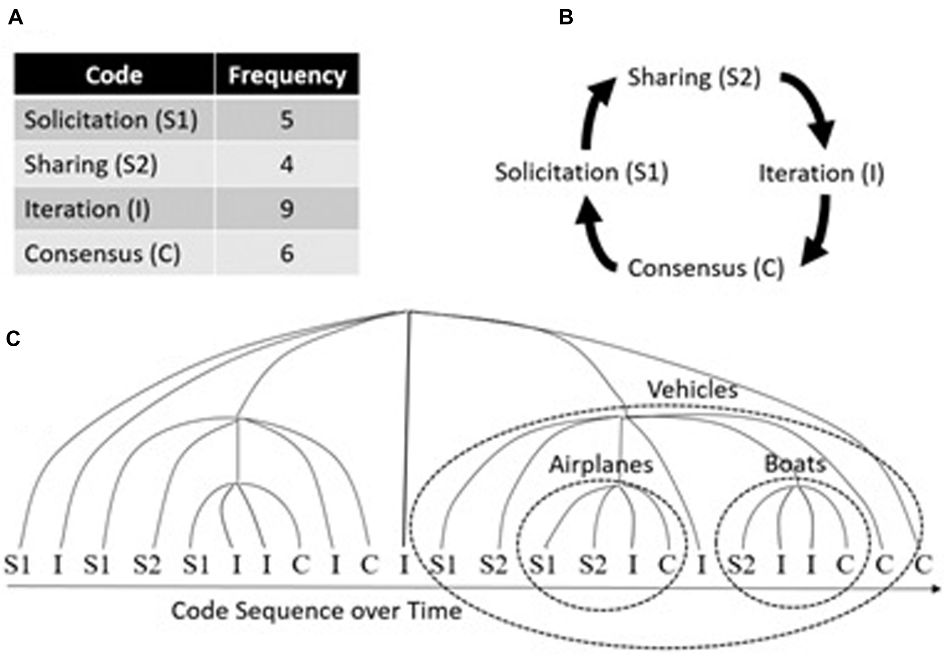

FIGURE 8 | (A) Code frequencies for the sample sequence of codes; **(B)** a simple linear transition (Markov) model of the most probable Lag-1 code transitions; **(C)** hypothesized temporal nesting (i.e., fractal structure) of code transitions organized around task-relevant communication.

occurrences of intervening codes at each scale size) to test for a power-law relationship (Brown and Liebovitch, 2010).

The results of this study indicated that communication specific to the type of team task exhibited fractal (power-law) scaling. Specifically, Fact-based communication was more fractal for action-based teams, and Interpretation-based communication was more fractal for decision-making teams. These results confirmed that the temporal nesting (i.e., fractal structure) of code transitions was organized around task-relevant communication. (As expected, Conversation Regulation was similar for both team types and did not exhibit temporal fractal structure).

To determine whether these patterns were generated by a self-organization process, we compared the power-law distribution fits to a memoryless Poisson process. Memoryless Poisson events are only locally variable (waiting time parameter) and follow an exponential distribution. Both Facts and Interpretations were significantly better fit by a power-law rather than an exponential function (there was no difference for Conversation Regulation). We think that the global self-organization of team communication commences when a system (team) is continuously balanced on the verge of change as new information is added (as the conversation evolves) at the local scale (i.e., self-organized criticality; Bak, 1996). Hence, the global order of conversation evolves out of locally variable communication inputs and evolves most clearly for task-relevant communication acts.

Systems characterized by self-organization also exhibit long-memory (Beran, 1994). Long-memory can be thought of as a type of memory that is not contained in individual elements of the system (e.g., working memory) but in the history of interactions among system elements (i.e., system-level memory). In terms of team communication, the presence of long-memory means that team members' interactions are not just intentional acts at a local scale but are informed by the history of interactions at the global scale. We have observed the development of long-memory effects in medical and military teams in terms of the coherence of their conversation as they communicate over time.

The Latent Semantic Analysis (LSA; Landauer et al., 1998) cosine measures the relatedness ("coherence") between any two pieces of discourse (e.g., any two utterances; any two transcripts; etc.). The timescale on which the cosine measure demonstrates coherence can be used to assess the characteristic timescale on which teams communicate knowledge, a measure of the long-memory of a team (Gorman, 2005). **Figure 9** shows how cosine (knowledge relatedness) diminishes as the timescale (distance between utterances) is increased for two medical teams (these teams are described in the study by Stevens et al., 2016). The steeper drop off for the team in the bottom panel suggests that their discourse has a shorter timescale of coherence (their conversation has a "shorter memory"); by contrast, the team in the top panel has a longer timescale of coherence (their conversation has a "longer memory"). In this between-team comparison, both teams performed a simulated medical procedure, but the team with shorter memory was a novice team, whereas the team with longer memory had significant experience working together.

Another study by Gorman (2005) used the LSA cosine method to investigate within-team changes in long-memory in UAV teams. Teams learned to take photos of ground targets

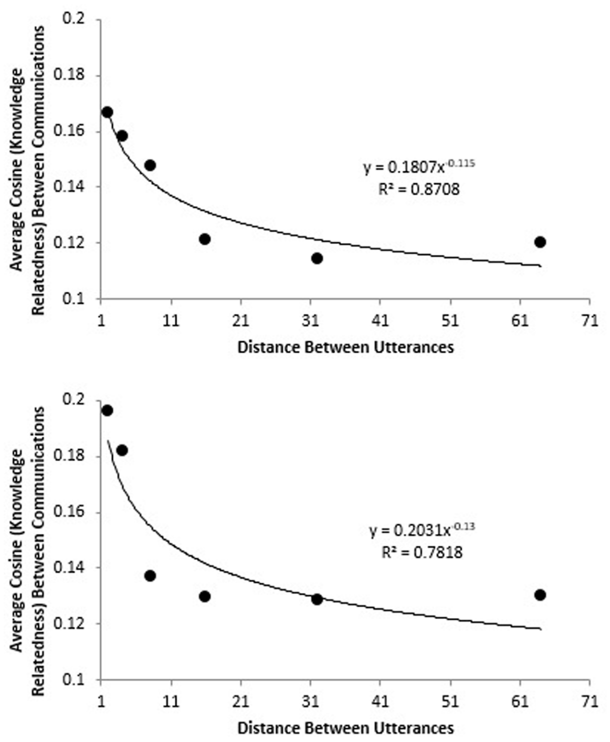

FIGURE 9 | These figures show how the knoweldge relatedness of communication diminishes as timescale (distance between utterances) increases. The communication of the experienced team in the top panel has more long-memory than the communication of the novice team in the bottom panel.

over five 40-min mission segments. The first four missions were low workload, followed by a high workload mission. The results indicated that the amount of long-memory in team communication increased from Mission 1 to Mission 4. In Mission 1, long-memory had not been established, and communication patterns were only locally variable. However, by Mission 4 long-memory had been established, such that team communication displayed persistence over short-to-medium timescales and anti-persistence over longer timescales. Like the inverted pendulum, there was an interplay between positive and negative feedback on local and global scales that structured team communication, which is a general characteristic of self-organized and long-memory processes. The long-memory effect weakened at Mission 5, however, indicating that the high workload condition may have regressed teams back toward a novel state, similar to Mission 1, before long-memory had been established.

The studies described in this section are consistent with Principle 1, that local variations in intentional communication behaviors are dynamically structured to maintain team effectiveness and coherence at the global scale. Moreover, we would argue that as with unintentional synchronization, global patterns in team communication can compel team members to interact in unexpected ways (Gorman and Cooke, 2011; Gorman, 2014). In combination with the studies described in the section "Team Dynamics at the Level of Perceptual-Motor Coupling," and in accordance with Principle 2, we see similar patterns of local-global dynamics at work across perceptual-motor and cognitive-behavioral levels of analysis. In the next section, we turn to Principle 3 by examining research on team dynamics across levels of analysis.

Cross-Level Effects between the Cognitive-Behavioral and Neural Levels of Analysis

In this section, we extend Principle 2 by tying dynamics together across neural and cognitive-behavioral levels of analysis (Principle 3). In particular, we describe our findings on cross-level effects wherein changes in communication patterns are associated with changes in neural patterns and how environmental perturbations simultaneously impact dynamic signals at both levels of analysis.

One way of examining neural processes in the context of team dynamics is by comparing them to simultaneous cognitive-behavioral processing in team cognition, such as team communication. When people communicate, their neural activity often becomes synchronized. This synchronization is present as a spatial and temporal correlation between the speaker and listener's neural activity (Stephens et al., 2010). This correlation occurs at a delay, often with the listener's neural activity preceding the speaker's neural activity (Stephens et al., 2010). It is argued that this neural coupling serves as a method for how brains successfully convey information between interacting individuals. In this context, *cross-level effects* examine how neural coupling, in the context of neural synchronization across team members, is affected by changes in team communication patterns (Gorman, 2014; Gorman et al., 2016).

Gorman et al. (2016) investigated cross-level effects in novice and experienced submarine crews. The communication variable was the LSA vector length, which quantifies the degree to which an utterance relates to the domain of discourse. The neural activity variable was the Shannon entropy (Shannon and Weaver, 1949) over a series of electroencephalography (EEG) neurodynamic symbols that describe the distribution of neural activity across team members. Neurodynamic entropy essentially indicates how much the neurophysiological distribution is changing across team members over time (Stevens and Galloway, 2014, 2016, 2017). The higher the entropy, the more the distribution of neural activity is changing; the lower the entropy, the less the distribution is changing, and the more neurally synchronized the team. Lagged cross-correlations between the LSA vector length of each utterance and mean entropy during each utterance were calculated to determine the presence of cross-level effects. Peak cross-correlations indicated that changes in communication patterns are immediately reflected in changes in neural synchronization for novice crews (i.e., peak cross-correlation at Lag-0) but that changes in neural synchronization tend to be preceded by changes in communication pattern for expert crews (i.e., lead-lag effects). This suggests that as people continue to work as a team, communication can influence neural coupling by dynamically entraining the distribution of neural activity across team members. Hence, team dynamics at the neural and cognitive-behavioral levels of analysis are coupled, and this coupling occurs across a temporal lag as team members continue to work together (Principles 2 and 3).

More evidence of cross-level effects can be seen in research on medical teams. Stevens et al. (2016) monitored EEG signals in surgical teams and measured their neurodynamic entropy while simultaneously capturing their communication activity. **Figure 10A** shows one team's discrete recurrence plot (discrete RP; Gorman et al., 2012a) of turn-taking during team communication. For a sequence x of length N, the discrete RP is an $N \times N$ symmetric matrix, where if the value of $x(j)$ is identical to the value of $x(i)$, then a dot ("recurrent point") is plotted at $x(i,j)$ in the RP. Note that the main diagonal in the RP is completely filled in because it is the one-to-one plot of the sequence against itself at $i = j$. Changes in how the dots cluster around the main diagonal indicate changes in communication flow (i.e., patterns of who is talking and when) over time. The amount of organization (i.e., how orderly vs. random) in communication flow can be measured by calculating the determinism (%DET) of the cluster of dots around the main diagonal. %DET is calculated as the number of recurrent points forming diagonals divided by the total number of recurrent points (we refer the reader to Shockley, 2005, for other measures that can be calculated). The black trace overlaying the RP in **Figure 10** is a moving window calculation of %DET around the main diagonal. Note the drop in %DET, or turn-taking organization, at about 1,000 s, which corresponds to a breakdown in communication when a fire broke out in the operating room (OR). As shown in **Figure 10B**, this behavioral breakdown as measured by a drop in %DET was associated with a contemporaneous drop in neural entropy in the team (spikes in entropy of communication codes have also been shown to be sensitive to changes in task dynamics; Wiltshire et al., 2017). Specifically, the communication breakdown precedes a negative spike in neural synchronization, which happens when a team mentally locks up due to environmental perturbations and indicates a re-organization of team neurophysiological state (Stevens and Galloway, 2016). Hence, as communication becomes disorganized, and then reorganized, the team's neural signals display an accompanying re-organization of system state at the neural level (Principle 3).

Having described in the section "Team Dynamics across Levels of Analysis" a series of results underpinning Principles 1–3, we turn to a discussion of the theoretical implications of the dynamical systems approach for conceptualizing psychological processes and human performance in teams.

THEORETICAL IMPLICATIONS OF THE DYNAMICAL SYSTEMS APPROACH TO TEAMS

First, it should be noted that the dynamical systems approach described in this article has many underpinnings in the history of psychology. These include psychological theories that embrace systems thinking, such as the ecological approach (Gibson, 1966), activity theory (Leont'ev, 1981), coordination dynamics (Kelso, 1995; including interpersonal, Richardson et al., 2005, 2007), distributed cognition (Hutchins, 1996), groups as complex systems (McGrath et al., 2000), interactive team cognition (Cooke et al., 2013), dynamical systems in team sports (Grehaigne et al., 1997; Bourbousson et al., 2010; Vilar et al., 2012; Cuijpers et al., 2015), non-linear dynamics in human factors and ergonomics (Guastello, 2017), and systems thinking in human factors (Chapanis, 1996) and human-computer interaction (Barnard et al., 2000). What is different about the dynamical systems approach to teams, and what does it offer team psychology?

Though there are many different approaches to understanding how systems in action affect human behavior, the dynamical systems approach to teams is primarily rooted in objective team coordination/performance metrics and mathematical representations that explain how interpersonal interaction lawfully relates to individual-level variability. One theoretical implication of this involves the so-called "slaving principle" (Haken, 1983), which is the control of system elements by an "order parameter" that captures global coordinative structure. Demonstrations of this principle can be found in interpersonal coordination research (e.g., Schmidt et al., 1990; Amazeen et al., 1995; Richardson et al., 2005, 2007; Ouiller et al., 2008; Gipson et al., 2016). In the context of the slaving principle, variability in individual behavior must be understood in the context of global coordination parameters (e.g., power laws and long-memory effects) that compel team members to behave in certain ways (Gorman and Cooke, 2011). A related implication involves how the perturbation of a system ripples through the system due to the interconnectedness of system elements. For human behavior, the important point is to understand how perturbing one or a few individuals affects and changes the behavior of other, connected individuals. We have empirically demonstrated this idea in training adaptive command-and-control teams (Gorman et al., 2010b; described later) but, moreover, this idea carries implications for how environmental change (broadly construed) impacts the thoughts and behaviors of people embedded in that environment.

Inheriting from some of our theoretical forerunners is that the dynamical systems approach to teams emphasizes the "psychology of active systems" rather than the "cognitive sandwich" (i.e., stimulus, cognitive processing, response) mode of explanation. The dynamical approach to teams focuses on real-time interactions as the appropriate level of psychological inquiry for understanding how other people and our surroundings structure thought and behavior. This is in contrast with the nostalgic view of psychology that aims to understand psychological processes by studying isolated individuals and only later adding real-time interactions as "context effects" once the solitary processes have been understood (Wertsch, 1991). As a matter of course, the difference in analysis is one of beginning with the system as a whole versus trying to integrate components into a system once the components are understood. The result of this is that explanations and models of human behavior that a dynamical systems approach provides (e.g., attractors;

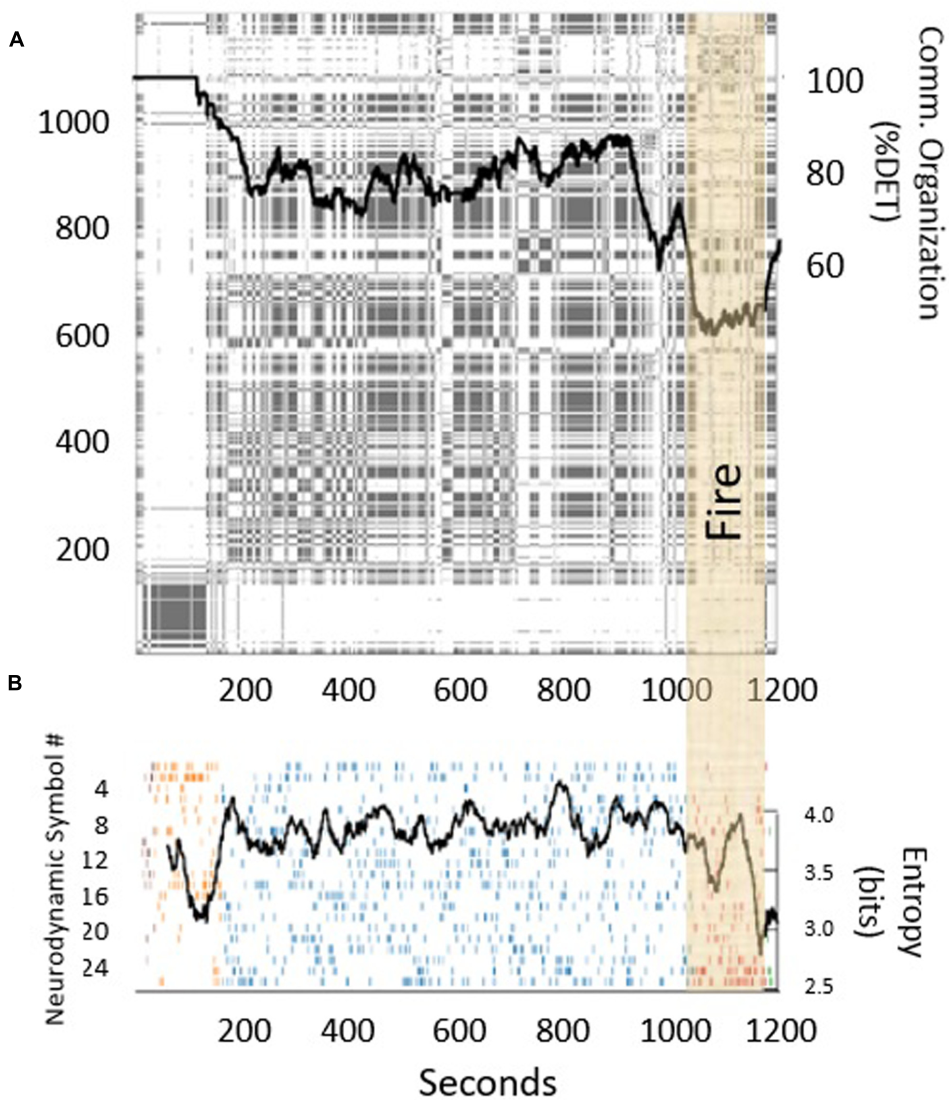

FIGURE 10 | (A) Discrete recurrence plot of speaker turn-taking in a medical simulation. The black trace measures the communication determinism (larger values mean more orderly; smaller values mean more random) around the main diagonal using a moving window of size 150. **(B)** The black trace measures the simultaneous neurodynamic entropy across team members.

long-memory) are unfamiliar to many psychologists and other students of human behavior, whereas traditional explanations and models (e.g., neurons; representations), although attractive to psychologists, do not contain the necessary information to understand how our thoughts and behaviors are shaped by the dynamic interpersonal interactions in which they are embedded.

As embodied in Principles 2 and 3, there is no preferred level of analysis for investigating team dynamics. The dynamics are present across levels of analysis, and the assumption of theory reduction (e.g., that the psychological must be reducible to the biological) and the accompanying bridge laws are not required. Put differently, there is no "fundamental substance" or "unit of analysis" in team psychology; everything is dynamic process (Thelen and Smith, 1994). This does not preclude observing dynamic process on one level of analysis while ignoring others, but it assumes that behaviors on unobserved levels of analysis are simultaneously being shaped by the same dynamics. Hence, the decision to analyze one level of analysis or even to decide what levels of analysis exist may seem somewhat arbitrary. In our experience, the first decision is based on the research question at hand (e.g., is it about overt behavioral acts, or is it about covert neural processes?) and the second is constrained by the equipment available to measure the dynamics (e.g., motion capture vs. voice recordings vs. EEG).

As with any method of inquiry, the dynamical systems approach carries its own characteristic language and style of argument that constrains the types of explanations it can offer (Quine, 1951). Theoretical ideas emanating from the dynamical systems approach to teams will tend to focus on how behavior changes through interpersonal interaction and how global interaction patterns come to structure individual thought and behavior. Moreover, there is no preferred level of analysis; the choice depends on the research question and careful selection of measurement equipment. This is in contrast to approaches that emphasize psychological processes that *must* be localizable within the individual and *must* be understood in terms of a fundamental substance or unit of analysis (e.g., brain function as ultimate theory reduction).

PRACTICAL IMPLICATIONS FOR TEAM TRAINING AND ASSESSMENT

Traditional approaches to team training including crew resource management (Helmreich et al., 1999) and cross-training (Blickensderfer et al., 1998) emphasize the alignment of team member knowledge, skills, and attitudes (KSAs; Salas et al., 2006) to enhance team performance. These approaches have been successful in enhancing team performance (e.g., Marks et al., 2002). We argue that the dynamical systems approach to team training can further enhance human performance under novel conditions in the post-training environment.

Perturbation training (Gorman et al., 2010b) is a team training approach that draws on the systems proposition that when a coordination pattern is perturbed, all team members (not just those directly affected by the perturbation) must readjust their interaction patterns at a local scale to maintain system stability and team effectiveness at a global scale (Principle 1). Well-placed perturbations (e.g., unexpectedly cutting a communication link) exercise the potential coordination space of a team beyond routine conditions by forcing them to develop new solutions for novel coordination problems. The prediction for team training is that by introducing perturbations during team skill acquisition, we increase the flexibility and adaptability of the team members, thereby enhancing team performance in response to novel and unpracticed task conditions. This training approach has precedence in the transfer of motor and verbal learning to novel situations (Schmidt and Bjork, 1992) and in training individual and team sports (Schöllhorn et al., 2006; Renshaw et al., 2010).

In the Gorman et al. (2010b) study, perturbation training led to superior performance under novel task conditions compared to cross-training and procedural training. Teams in the cross-training condition developed shared knowledge to a greater degree than teams in the other conditions and performed just as well as perturbation-trained teams on tests of routine task performance. Compared to cross-training and perturbation training, procedural training led to the least effective teams under both routine and novel task conditions. However, performance under novel task conditions was enhanced through perturbation training compared to both cross-training and procedural training. We think that flexibility in real-time interaction processes induced by perturbation training, rather than shared knowledge or following scripted procedures, enhances team performance by exercising the real-time dynamics that team members need to experience in order to adapt in the post-training environment.

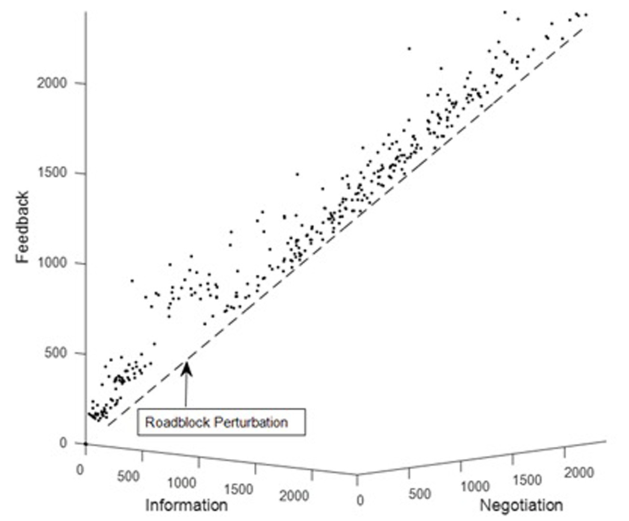

FIGURE 11 | Measuring the team response to a roadblock ("relaxation time") as a method for team assessment.

Perturbing team coordination is closely related to a systems approach for measuring team situation awareness (team SA; Gorman et al., 2005, 2006; Cooke et al., 2009). This approach involves identifying "roadblocks," which are novel or unlikely task conditions that require an adaptive and timely coordinated response in order to maintain team effectiveness. In this approach, team SA is assessed as a team's ability to team overcome roadblocks in a timely manner (Cooke and Gorman, 2009). **Figure 11** shows how the timing of the components of the UAV coordination score from **Figure 7** (the dots) are altered by a roadblock. Under routine task conditions, the dots gravitate toward the diagonal line (the attractor). Roadblock onset occurs at about 500 s, and the dots are "pushed" off the attractor (diagonal line) by the roadblock, corresponding to an alteration of the routine coordination pattern. Two measures of team SA in response to a roadblock are whether the team overcomes the roadblock (i.e., whether the dots gravitate back toward the diagonal line) and the time to overcome the roadblock (i.e., how long it takes for the dots to gravitate back toward the diagonal line). The latter assessment is related to the dynamical concept of *relaxation time*, which is essentially the time it takes for a system to return to its attractor after its trajectory has been perturbed. In actual teams, a roadblock could have catastrophic consequences if a team has a long relaxation time and does not respond appropriately and in a timely manner. For practical purposes, real-time analysis of team coordination can help prevent catastrophic errors caused by delayed team responses.

Team communication, cognition, and coordination give rise to dynamic patterns that change in real time. Breakdowns and unexpected changes in these processes are at least partially responsible for the Challenger Shuttle disaster (Vaughan, 1996),

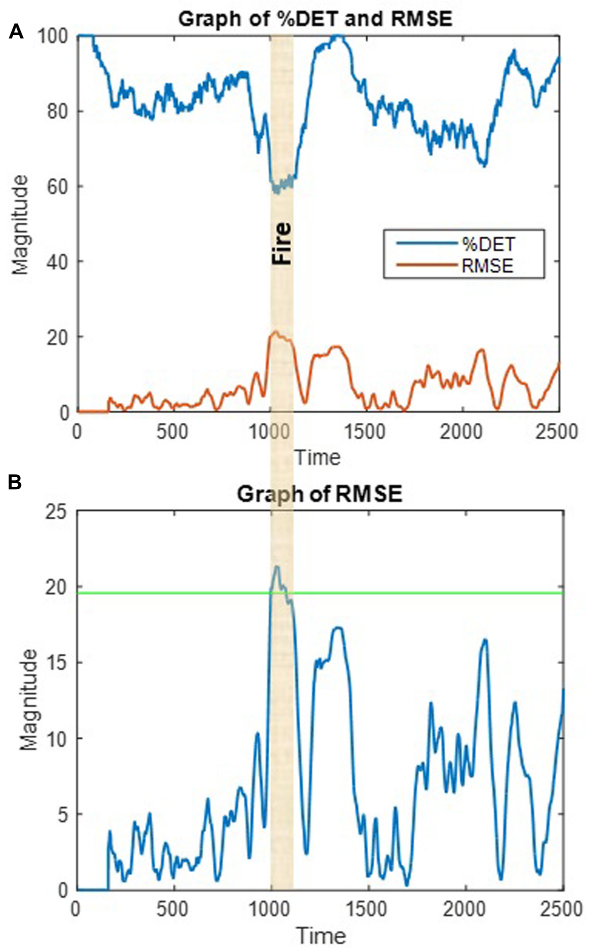

FIGURE 12 | (A) Graph of communication determinism (%DET) and root mean square error (RMSE) from a prediction model; **(B)** RMSE relative to a 99% confidence interval (green line) indicates a significant fluctuation in communication pattern (drop in %DET) in response to the fire in the OR.

delayed response times to Hurricane Katrina (Leonard and Howitt, 2006), and poor communication in air traffic control in response to the September 11th attacks (Kean and Hamilton, 2004). For team assessment, it is important to detect these breakdowns and roadblocks as they unfold in real-time (Gorman et al., 2012b).

The assumption behind real-time dynamics is that we can meaningfully analyze team interaction data *ad hoc*, as it becomes available, as opposed to *post hoc* (Gorman et al., 2012b). This is plausible due to the "historical" quality of team interaction, such that team communication has long-memory. That is, a current observation in a team communication time series is not independent from previous observations—teams have *momentum* (Den Hartigh et al., 2014)—and this creates temporal dependencies that can be quantified using dynamics (Smith et al., 2008; Gorman et al., 2012b).

We have been successful in developing methods to detect teamwork breakdowns and roadblocks in near-real time using turn taking patterns during team communication in different real-time contexts (Gorman et al., 2012b; Grimm et al., in press). Using the non-linear prediction algorithm described by Kantz and Schreiber (2004), we stream in a communication variable and scan it to detect fluctuations in communication patterns that significantly differ from previous observations of the communication variable. The assumption is that as in **Figure 11**, significant fluctuations in team communication patterns correspond to significant environmental perturbations that require a timely response. To illustrate, **Figure 12A** reproduces the determinism time series from **Figure 10A** (top trace) from the surgical team study along with the root mean square error from the non-linear prediction algorithm (bottom trace). The root mean square error is also plotted in **Figure 12B** relative to a 99% confidence interval, which indicates that the fire in the OR corresponded to a significant perturbation to the team's communication dynamics. Once a significant perturbation is detected, if the team is responding adaptively, then we expect the prediction error to return to a non-significant level in a timely fashion. If not, then some form of outside intervention might be required to effectively address the situation. If the team does not respond at all to a significant environmental perturbation (such as a fire in the OR), then this could reflect a deeper operational issue in need of remedial training.

Real-time analysis is useful for detecting change in dynamical systems in response to a significant environmental perturbation. Applications of real-time analysis can potentially identify significant and harmful changes in the team environment to ensure they are acted on in an appropriate and timely manner. The above illustration described a method of real-time analysis as applied to team communication. However, there is potential for these methods to be applied to perceptual-motor and neural levels of analysis such as those described in other sections of this article (i.e., application of Principles 2 and 3).

CRITICISM OF THE DYNAMICAL SYSTEMS APPROACH AND FUTURE DIRECTIONS

Dynamical systems approaches in psychology have been cautioned to avoid the mistake of drawing generalizations about psychological processes simply because they carry a particular dynamical signature (Rosenbaum, 1998). This is followed by the more general criticism that there is no psychological "mechanism" responsible for producing the dynamics (see Van Orden et al., 2003 for a discussion). Here, mechanism means something like a neural pathway or information-processing component (e.g., working memory) within the individual. Hence, one issue with the dynamical systems approach is that it does not naturally align with the mechanism-within-the-individual explanation so often sought in psychology. Because it is all about process and interaction, the dynamical systems approach operates at the systems level of explanation. From a traditional (e.g., cognitivist) perspective, thinking about how to change behavior at the individual level, for example, could be problematic from a dynamical systems perspective.

An example is the development of training programs that seek to alter a worker's KSAs in order to improve performance and outcomes (Salas et al., 2006). In the standard approach, the KSAs to be trained should be understandable to both the trainer and the trainee. The reason for this is that we must be able to understand what we are doing incorrectly if we are to change our behavior, and we must be able to observe whether our behavior has actually changed. But if behavior is a function of real-time interactions and not just KSAs, how do we change it? Turning to dynamics, it seems difficult to identify a particular KSA that we can instruct individuals on to, say, alter the long-memory effects or power laws that inform their behavior. While we can observe changes in the dynamics, it could prove challenging to provide instructions to an individual about how their local behavioral variability contributes to and is constrained by global dynamics over long timescales.

Individual training is critical, but it is only realized in the context of real-time interpersonal dynamics between an individual and their teammates, where constructs such as KSAs must be understood in the context of the stable states of a team's attractor dynamics. Formal equations of change in individual psychological states embedded in the interactions of dynamical systems have predicted individual variation in domains such as personality (Nowak et al., 2005) and marital satisfaction (Gottman et al., 2002), and similar equations have been written for teams (Guastello, 2017). As Nowak et al. (2005) point out, individual-level properties, such as KSAs, can give meaning to or modulate global dynamics, but more precisely, an individual's behavior is variable in order to converge on stable states of the entire system (Principle 1).

Within the context of the dynamical systems approach, individual thought and behavior are a function of real-time team interactions, in which KSAs or other individual-level properties are embedded. Individual-level properties are considered "intrinsic dynamics" and are a part of the initial conditions of the system (Nowak et al., 2005), but the way that thought and behavior play out can only be realized in the context of real-time team interactions. Returning to the concept of "mechanism," future research should not try to isolate dynamical principals in terms of reductionist psychological mechanisms such as working memory or pools of attentional resources. Rather, the notion of a psychological mechanism must continue to be extended to include dynamical principles that structure individual-level variability. Dynamical mechanisms (Peng et al., 1995) include attractor formation and dynamics, synchronization, and fractal scaling of thought and behavior. Future research should continue to study these "systems-level" psychological mechanisms through methods such as perturbation training and real-time team communication dynamics, as described above.

Separate from this, we think there are some interesting future directions that the dynamical systems approach entails from a cognitivist perspective. For example, investigating the questions of What do people actually know about the dynamics they produce, and Can they learn to control them? might enhance training at the level of individual-level properties. In terms of training, answering these questions could allow for the control of unintentional behaviors that interpersonal dynamics produce (e.g., spontaneous synchronization) and might provide individuals insight into the global, systems-level nature of their local behaviors (e.g., how their local behaviors are constrained by global coordination patterns). One might think of this as metacognition for systems or, perhaps, systems thinking from the perspective of an element within the system.

CONCLUSION

In summary, it is important to recognize how interactions shape our thoughts and behaviors. It is critical to understand this because so much of what we do involves interacting with other people and technologies that automate what people do. Dr. Martin Luther King Jr once wrote, "We are caught in an inescapable network of mutuality. . ..Whatever affects one directly affects all indirectly" (King, 1963). Ultimately, we think that understanding how dynamic interaction processes shape our thoughts and behaviors is a fundamental psychological question that is at the heart of understanding human nature.

In this article we have presented dynamical systems concepts and how they can be used to understand and model teams. Our results thus far have converged on three principles underlying human performance in teams. We present them in abbreviated form here:

(1) Local variability ensures global stability and vice versa.
(2) These dynamics are substrate-independent; there is no preferred level of analysis.
(3) Cross-level effects occur between levels of analysis.

That global team patterns vary in predictable ways is not a proxy for individual KSAs that have to exist in order to perform a task, but it provides systems-level explanations for how real-time interaction processes shape thought and behavior. Where, then, does team behavior come from? Based on our research, we think that the ontology that interpersonal behavior and teamwork are somehow encoded in the individual is inaccurate; rather, what is encoded in the individual emerges out of a vibrant network or interpersonal, social, and cultural interactions that continuously shape and reshape that which is encoded (Bakhtin, 1986). From this perspective, not just teams but individuals in any interactive environment can be understood and modeled using a systems approach.

AUTHOR CONTRIBUTIONS

JG primarily wrote the paper. TD assisted with the cognitive-behavioral and cross-level effects sections. DG assisted with the real-time analysis section. CG assisted with the dynamical concepts and unintentional synchronization sections. All authors contributed to the conceptualization and outline of the paper.

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An Integrative Perspective on Interpersonal Coordination in Interactive Team Sports

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Interpersonal coordination is a key factor in team performance. In interactive team sports, the limited predictability of a constantly changing context makes coordination challenging. Approaches that highlight the support provided by environmental information and theories of shared mental models provide potential explanations of how interpersonal coordination can nonetheless be established. In this article, we first outline the main assumptions of these approaches and consider criticisms that have been raised with regard to each. The aim of this article is to define a theoretical perspective that integrates the coordination mechanisms of the two approaches. In doing so, we borrow from a theoretical outline of group action. According to this outline, group action based on a priori shared mental models is an example of how interpersonal coordination is established from the top down. Interpersonal coordination in reaction to the perception of affordances represents the bottom-up component of group action. Both components are inextricably involved in the coordination of interactive sports teams. We further elaborate on the theoretical outline to integrate a third, constructivist approach. Integrating this third approach helps to explain interpersonal coordination in game situations for which no shared mental models are established and game situations that remain ambiguous in terms of perceived affordances. The article describes how hierarchical, sequential, and complex dimensions of action organization are important aspects of this constructivist perspective and how mental models may be involved. A basketball example is used to illustrate how top-down, bottom-up and constructivist processes may be simultaneously involved in enabling interpersonal coordination. Finally, we present the implications for research and practice.

Keywords: teamwork, shared mental model, affordance, group action, cognition, theory, environment

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INTRODUCTION

Interpersonal coordination is of primary relevance whenever sports teams perform interactively. The term "coordination" refers to the dynamic arrangement of contributing units to achieve a larger function (Gorman, 2014) and includes the organizing of team members' interdependent actions in regard to sequence and timing (McEwan and Beauchamp, 2014; see also Salas et al., 1995; Marks et al., 2001; Rousseau et al., 2006; Eccles and Tran, 2012). When teams succeed in coordinating their aggregated resources effectively, they can optimize the parameters that are relevant to their performance. One example of this is an enhanced area coverage in defensive football situations.

Another example is the optimized distribution of team network nodes, which improves passing opportunities for the members of a team. In practice situations, interpersonal coordination can be established through centralized monitoring by a coach who provides external feedback in real time (Seiler, 2014). This feedback can include upcoming play selections or adjustments in location and timing (Eccles and Tran, 2012). During a competition, however, interpersonal coordination is usually not based on guidance by one central authority (e.g., the coach). Distracting noises, distance and rule restrictions can prevent teams from being directed by external feedback. In such cases, more distributed or decentralized communication channels become important (Pedersen and Cooke, 2006; LeCouteur and Feo, 2011; Passos et al., 2011; Seiler, 2014). In the competitive setting of many team sports, a high physical workload and, most importantly, time constraints impede communication-based action regulation via closed feedback loops (Cannon-Bowers and Bowers, 2006). Understanding how coordination can nonetheless be achieved in these situations is important. However, the reciprocal and dynamic relationship between the social and individual factors involved in interpersonal coordinative processes make it obvious that human interaction in social contexts is among the most complex challenges to scientific understanding (Vallacher and Nowak, 1997; see also Birrer and Seiler, 2008; Duch et al., 2010; Carron et al., 2012; McEwan and Beauchamp, 2014).

Various perspectives and empirical approaches have emerged with which to explain interpersonal coordination in team sports. Two of these approaches are central to this article. The first is the concept of shared mental models (e.g., Cannon-Bowers et al., 1993; Eccles and Tenenbaum, 2004; Cannon-Bowers and Bowers, 2006). We refer to the second approach as the ecological perspective. This perspective highlights the importance of the information sources provided by the environmental context within which a behavior is performed (e.g., Araújo et al., 2006). This article begins by outlining the general assumptions of both perspectives and their associated criticisms. It then explains why both offer indispensable information with which to understand interpersonal coordination in sports teams and illustrates the need for an integrative perspective. In our attempt to integrate the central tenets of both these perspectives into a unified view of interpersonal coordination in team sports, we borrow from a theoretical outline of group action (Cranach et al., 1986). We elaborate on this theoretical outline to integrate a third perspective. This perspective focuses on the cognitive constructive organization of the situational game context. We argue that this third perspective is necessary to explain interpersonal coordination in situations for which no shared mental models are established and task situations that remain ambiguous in terms of perceived affordances. A basketball game sequence illustrates the theoretical considerations in an applied example. The article ends with concluding remarks and the implications of the presented perspective for research and applied practice.

Theories of Shared Mental Models

Theories involving concepts of shared mental models are rooted in a social-cognitive framework (Eccles and Tenenbaum, 2004, 2007). They build on the key tenet that the organization of individual and team behavior involves knowledge-based mental models (Rentsch and Davenport, 2006; Araújo and Bourbousson, 2016). According to theories of shared mental models, interpersonal coordination builds on individual team members' regulating their contributions based on inter-individually shared ground. Sharedness, within this line of research, has been referred to as the synergistic aggregation of the team members' mental functioning, especially in terms of similarity and complementarity (Langan-Fox et al., 2004; see also Levine et al., 1993; Klimoski and Mohammed, 1994; Hutchins, 1995; Cohen and Bailey, 1997; Mathieu et al., 2000; Cooke et al., 2003; Reimer et al., 2006; Stanton et al., 2006; Ward and Eccles, 2006). The development of shared mental models is assumed to improve team performance by enabling nonverbal interactions and implicit coordination (Cannon-Bowers and Bowers, 2006; Rico et al., 2008; Blickensderfer et al., 2010; Cooke et al., 2013). Overt interaction between the various team members thus becomes redundant.

We focus on two factors that are believed to be involved when shared mental models facilitate interpersonal coordination. The first is the feeding forward of behavioral instructions for defined game situations (Eccles, 2010). Plans (Schank and Abelson, 1977) have often been mentioned in this connection. In team sports, macrolevel plans refer to overall team plans and strategies (Eccles and Tenenbaum, 2007). Microlevel plans include more detailed information about the individual operations required in given situations. Plays in American football are prototypical of plans at the microlevel of team operations (Eccles and Tenenbaum, 2007). While microlevel plans further specify and confine behavior, they too must be adapted to the characteristics of the situational game context (Eccles and Tenenbaum, 2007; Macquet and Kragba, 2015; Gershgoren et al., 2016). We adopt the term "top-down" to indicate that knowledge-based shared mental models feed forward information that leads to interpersonal coordination.

In a questionnaire-based study investigating shared mental models in ice hockey and handball teams, Giske et al. (2015) found support for the existence of common attack patterns specific to certain kinds of game constellations. Overall, however, empirical sports studies using shared mental models remain scarce (Gershgoren et al., 2013).

For team plans to feed forward behavioral instructions, they must exist prior to the athletes' involvement in specific game situations. Because the situational game context is dynamic and may often be unique in its configurational setting, pure reliance on pre-existing and shared plans will not always be possible (Araújo et al., 2006; Eccles and Tenenbaum, 2007; Cooke et al., 2013; Silva et al., 2013). To account for this, theories of shared mental models have posited more dynamic and implicit ways in which multiple team members' mental models can overlap in real time (Eccles and Tenenbaum, 2004; Blickensderfer et al., 2010; Eccles, 2010; Eccles and Tran, 2012). Athletes are believed to use incidentally shared knowledge of probabilities to attribute situational informers to changes in task requirements and team members' reactions to these (Ward and Williams, 2003; Williams and Ward, 2007; Eccles, 2010). The importance of multiple athletes perceiving game situations and one another's behaviors in correct, anticipative and complementary ways is highlighted (e.g., Reimer et al., 2006). Empirical support for the role of shared knowledge in the implicit coordination in team sports has been provided by Blickensderfer et al. (2010). These authors used the degree to which teammates adjust their positioning with respect to one another as an indicator of the teams' implicit coordination. They found that the degree of shared expectations of specific doubles-partner responses was correlated with teams' implicit coordination during tennis matches.

Concerns have also been raised in regard to explaining this kind of in-process coordination (Eccles and Tenenbaum, 2004) by means of shared mental models. Skepticism has been expressed concerning the reduction of team coordination processes to collective team member states (Bourbousson et al., 2011; Gorman, 2014). Sharing a common perspective on specific game situations is unlikely to occur due to differences in knowledge, skill, history and position in physical space between players (Cooke et al., 2013; see also Reimer et al., 2006; Bourbousson et al., 2011, 2012; Macquet and Stanton, 2014).

The Ecological Perspective on Team Coordination

The approaches that we have subsumed within the ecological perspective share a focus on the environment in which team members must coordinate their behavior. In a very general sense, ecological perspectives stand in contrast with the idea of team members selecting options from those stored in mental models. Instead, ecological perspectives seek to show how the environment contributes to the kinds of interactions that occur between agents and their respective environments and to understand the properties of the environment that affect action and decision-making processes (Cutting, 1982; Greeno, 1994; Araújo et al., 2006; Araújo and Davids, 2009; Fajen et al., 2009; Vilar et al., 2012). We will adopt the term "bottom-up" to indicate that information from the environment leads to interpersonal coordination.

Gibson (1977) coined the ecological perspective by introducing the concept of affordances. By definition, affordances are opportunities to act that are directly perceivable in the environment in the here and now. By building a dynamic transactional system with their environment, athletes may perceive the environment's intrinsic meaning for behavior in terms of the environment's functional relationship to themselves (Gibson, 1979; Araújo et al., 2006). Because this is assumed not to require cognitive mediation, the role of mental models is subordinated (Gibson, 1977; see also Greeno, 1994; Araújo et al., 2006; Fajen et al., 2009).

The concept of affordances has been adopted to explain interpersonal coordination in sports teams (Silva et al., 2013). Here, the environment refers to the situational game context, which continuously changes with the behavior of the team members and their opponents. The situational game context thus constantly lays out new temporary environments and constrains the team members' possibilities in terms of coordinating their actions toward the achievement of performance goals from moment to moment. For example, previous actions will impact the options for moving on in the future. An inexact pass, a badly chosen path on the playing field or inappropriate positioning can all affect the options for action available at any given point in time (Nitsch, 2009). The remaining options that afford ways of approaching a team goal in common facilitate interpersonal coordination in a bottom-up fashion (Araújo et al., 2006). Thus, affordances are highlighted as the organizing elements that continuously provide information about how team members can coordinate within the situational game context (Fajen et al., 2009).

Empirical support for the role of the situational game context in decision making during interactive team sports has been provided by Correia et al. (2012). Using a simulated 3 vs. 3 rugby task, they found that gaps opening in particular running channels in the defensive line influenced the ball carriers' decisions to pass to either Team Member 1 or Team Member 2 or run with the ball. In a study analysing passing behavior in real-world soccer competitions, Steiner et al. (2017) found that passes were affected by the team members' positioning relative to the ball carrier, the openness of passing lanes leading to team members and the team members' degree of defensive coverage by opposing players. The findings indicate the athletes' recurring use of the same perceptual information to make passing decisions.

We should mention that the guiding role of the situational game context has also been emphasized in conjunction with perspectives that do not explicitly restrict the relationships between agents and their social context to perceptual means (e.g., Gorman, 2014; McNeese et al., 2016). According to such perspectives, the causal mechanisms of team coordination lie in the dynamic process of team interaction (Gorman, 2014). This dynamic process may include reciprocal communicative acts between team members.

If athletes perceive multiple affordances within a situational game context, this situational game context remains ambiguous, and behavior is virtually unconstrained by the perceived affordances (Cutting, 1982). Ecological perspectives have been criticized as being unclear about how specific affordances for interpersonal coordination are selected from a multitude of possibilities (Norman, 1999; Beek, 2009; Nitsch, 2009). Furthermore, the observation of two performers coordinating their behaviors with one another does not clarify what the perceived affordance was for either performer or what information constrained the link between them (Araújo and Bourbousson, 2016). To address these criticisms, it has been proposed that the notion of people as agents in ecological theories should not be reduced to the bare person-environment relationship (Cutting, 1982; Nitsch, 2009). Instead, the organizing principles of perception and situational orientation should also be applied to the processes that operate within the actors (Cutting, 1982; Greeno, 1994; Gobet, 1998; Didierjean and Marmèche, 2005; Nitsch, 2009). For example, rather than endorsing or rejecting the roles of cognition and internal representations programmatically, Nitsch (2009) has called for specifying the conditions under which they might or might not be useful. We will take up on this notion in Section Elaborating on the Outline.

Illustrating the Need for an Integrative Perspective

Lately, there has been a growing call for an integrative perspective on interpersonal coordination. For example, McNeese et al. (2016) state that individual and shared mental models are important because not all actions in interdependent team sports are directed by the environment. They argue for the necessity of better integrating perspectives on shared mental models and ecological perspectives to capitalize on the strengths of each in the understanding of interpersonal coordination in sports teams. Gorman (2014) states that a general theory of interpersonal coordination should involve intention and knowledge on the part of team members while also considering environmental constraints as fundamental to interpersonal coordination (see also Araújo et al., 2006; Pedersen and Cooke, 2006; Duarte et al., 2012; Cooke et al., 2013).

To illustrate the need for an integrative perspective in the context of team sports, one can recall how often strategies and plans are discussed in practice sessions (Gershgoren et al., 2013; Giske et al., 2015). Teams practice defensive behaviors, specific strategic alignments in response to the opposing team's behavior, to near perfection. Offensive plays to be announced during games are also rehearsed. This kind of pre-process coordination (Eccles and Tenenbaum, 2004, 2007), which builds up shared mental models, is so omnipresent in team sports that excluding it from a theory of interpersonal coordination will certainly result in painting an incomplete picture. Furthermore, it is common practice to rehearse specific modules of coordinated team plays, which can be flexibly adapted to many game situations. So-called "give-and-goes" are an example from basketball. In a give-and-go, an athlete passes (gives) the ball to a team member. The athlete then immediately runs (goes) to a new spot to offer himself as an opportunity to pass the ball again (Eccles and Groth, 2007). In soccer, players practice dynamically positioning themselves in a triangular alignment. This way, passing opportunities for the ball carrier can constantly be maintained (Giske et al., 2015; for further examples, see Eccles and Tran Turner, 2014).

On the other hand, a theory of interpersonal coordination must incorporate the fact that coordination always occurs within specific and sometimes unpredictable game contexts. Hence, the role of the information provided by that situational game context is paramount. Sometimes, athletes who are perceptually attuned to their team and game contexts may be able to perceive these contexts directly by means of the acts they afford. For example, Fajen et al. (2009) point out how an open passing lane to a team member affords a pass to this team member. At the same time, passing lanes that are well-defended by opposing players perceivably constrain passes (Steiner et al., 2017).

In this article, interpersonal coordination that is directed by shared mental models or enabled by the perception of affordances frames our integrative perspective. We argue that team coordination is also established in situations for which shared mental models are not established and situations in which athletes cognitively process the information provided by the situational game context. Indications that such situations do occur in the context of team sports can be seen in a line of qualitative research involving interview techniques such as video-stimulated recall (e.g., Sève et al., 2005; Poizat et al., 2009; Bourbousson et al., 2010, 2011, 2012). Video recordings of team behavior in natural settings and verbalizations during post-match interviews are used to understand how individuals construct meaning in game situations. These retrospective verbalizations indicate that in mental models, sharedness is not always achieved (e.g., Poizat et al., 2009; Bourbousson et al., 2011, 2012). They further indicate that athletes take into account multiple situational factors, mobilize prior knowledge and combine these to construct new knowledge about the situational game context (Sève et al., 2005; Poizat et al., 2009; Bourbousson et al., 2011).

In the following sections, we will develop an integrative perspective on interpersonal coordination in interactive team sports. This integrative perspective has no intention of altering or criticizing existing theories. Instead, team coordination *exclusively* directed by shared mental models, as opposed to that *exclusively* directed by the perception of affordances, will serve as the theoretical poles of the integrative work. In Section A Theoretical Outline of Group Action, we summarize the theoretical outline of group action by Cranach et al. (1986), which serves as a framework for our integrative perspective. The outline views group action as both directed by team plans and reactive to the situational game context. Thus, both top-down and bottom-up processes play important roles in the regulation of team behavior. In Section Elaborating on the Outline, we further elaborate on Cranach et al.'s outline (1986) and explain how interpersonal coordination can be established in situations that do not fit either of the theoretical poles. Following Nitsch's (2009) call, we have considered the ways in which information from the situational game context can contribute to the emergence of interpersonally coordinated behavior in ways that go beyond the information's most direct link to agents via the perception system. The roles of mental models in the subjective organization of situational opportunities to co-act will therefore be discussed.

A THEORETICAL OUTLINE OF GROUP ACTION

Cranach et al. (1986) consider teams to be self-active systems that actively direct their behavior toward certain ends. The impact of external factors (e.g., through the perception of situation-specific information) is considered an integral part of directed behavior. However, team action is not affected only by external information. It is also instantaneously guided by internally stored information (e.g., cognitively represented team plans). Thus, perceptual and cognitive processes are both involved in the system's monitoring of external contexts and the steering of behavior.

Cranach et al. (1986) argue that because it is based on individual goal-directed behavior, team action possesses the same characteristics as individual action but is complemented by additional features that stem from its social nature. These additional features are communicative and cooperative processes that become possible and necessary through the involvement of multiple persons. Cranach et al.'s theoretical outline of group action is built on four central components: the *structure of the task*, the *structure of the team*, the *information-processing structure* and the *action execution*.

The structure of the task and the structure of the team are essential in defining the conditional framework for team efficiency. For optimal performance, team and task structures must be in accord with one another. Cranach et al. (1986) define a *task* as a social demand that requires an actor to act. For the most part, tasks are closely related to specific ecological settings (e.g., a specific game situation). Insofar as the task contains detailed information about goals and plans, Cranach et al. speak of a task *structure.* By this definition, task structures are not determined simply by the information available in specific game situations. Instead, the information available in the situational game context is complemented with internalized scenarios, e.g., mental models that include goals and goal-directed plans that are viable means of task performance.

Team structures, on the other hand, are associated with the formation of a team, including the assignment of all team members to specific task-relevant functions and the relationships between team members during their involvement in a single interactive task. In some sports (e.g., sailing), the team structure is clear because the team members' roles are distinctly attributable to a set of predefined subtasks. In most interactive sports, however, general role assignments do not predefine specific functions in all situations down to the last detail. Instead, the required functions must be specified in relation to the constraints of situational game contexts, which often appear at short notice. Thus, team members must adapt their behavior according to the current task structures.

The *information processing structure,* the third component of the model, describes the processes underlying the team members' adaptation to changing task structures. Team-action-related information processing takes place at both the individual and team levels. On the level of individual team members, the theory considers cognitive information processing, which is viewed as a unique instrument for the mental guidance of goal-directed action.

Communicative processes complement cognitive information processing in individuals. Cranach et al. (1986) refer to this as information processing at the team level. Commands and assisting calls represent the flow of information between team members[1]. Moreover, the communication of an individual perception can affect the situational orientation of the team[2]. Cranach et al. also note that communication enables teams to learn action schemata for future acts. This exactly corresponds to the kind of pre-process coordination referred to by Eccles and Tenenbaum (2004, 2007).

The model's fourth component is *action execution.* Team behavior consists of individual acts and social execution. Appropriately executed and mutually coordinated individual acts allow interpersonal coordination to emerge at the team level. Cranach et al. (1986) argue that individual action is organized along three dimensions: hierarchy, sequence and complexity. While the authors explain the dimensions' relevance to individual acts, we will later illustrate how the same dimensions can be considered as organizing dimensions of interpersonally coordinated team behavior.

Finally, Cranach et al. (1986) argue that groups often perform within equifinal task situations (Heider, 1958). Equifinality refers to the fact that the completion of complex team tasks is usually not restricted to one unique solution. Instead, many potential paths conceivably allow attaining the same goal (see also Oesterreich, 1981). This flexibility can be advantageous because it enables teams to approach given requirements in light of existing team abilities. On the downside, equifinality complicates the emergence of interpersonal coordination because it increases the degrees of freedom. Furthermore, the behavior of opposing teams becomes more unpredictable.

ELABORATING ON THE OUTLINE

To elaborate on our view of the involvement of internal information in the subjective construction and organization of the information provided by the situational game context, we adapt and extend Cranach et al.'s (1986) ideas. We will discuss two factors we consider central in regard to this internal information: organizational rules and the contents of mental models.

Organizational Rules

In order to explain how situational opportunities for interpersonally coordinated team behavior are established through a team member's interaction with a situational game context, we adopt Cranach et al.'s (1986) notion of the three-dimensional organization of action and apply it to the organization of interpersonally coordinated team action. Because it is directed toward the attainment of primary team goals, individual behavior requires reactive adjustment to the situational game context and constant (re-)organization along hierarchical, sequential and complex dimensions. While all three dimensions of action organization supposedly act in combination, we will briefly explain their features separately.

The hierarchical aspect of team action organization refers to monitoring a situation's functional relationship to the attainment of the primary goals that are currently directing behavior. From an athlete's point of view, this includes determining a situation's offerings in regard to the highest task goals, which provide the athlete's directional perspective (Araújo et al., 2006; see also Klein et al., 2007; Nitsch, 2009). In team sports, this directional perspective is set out by the general rules of the specific sport. If the main objective is to score more points than the opposing

[1]Note the similarity to Cooke et al's (2013) conceptualization of interactive team cognition.

[2]Note the similarity to the concept of shared situation awareness (e.g., Macquet, 2016).

team, then scoring points and preventing opponents from doing so define the two goals that direct behavior at the highest level of the hierarchy. The team must adopt a structure (e.g., assign functions to team members) and perform behaviors that are optimally suited to attaining these goals.

During task performance, the situational constraints organized by the opposing team may block instant paths to the primary goal of scoring. Consequently, situational game contexts must be monitored concerning the sequentially and complexly organized goal approximations they allow. Preparatory steps, such as bringing the ball to a shooting position nearer to the target, become necessary (Oesterreich, 1981). These preparatory steps give rise to subgoals at lower levels of the hierarchy. Subgoals are abandoned when achieved and then replaced by those that follow in the sequential alignment toward higher-order goals (Wilensky, 1983). If the situational game context changes in a way that enables a more direct path to higher-order goals, then temporary subgoals may be abandoned before they have been reached (Oesterreich, 1981). The relationship between lower- and higher-level goals determines the hierarchical-sequential organization of team behavior (Volpert, 1982; Cranach et al., 1986; Marks et al., 2001; see also Hacker, 2005).

The dimension of complexity complements the goal-directed organization of team behavior. We extend Cranach et al.'s (1985, 1986) use of the term (they use it to describe multiple simultaneously performed acts of a single individual, e.g., moving one's head and feet) and use it to refer to the simultaneous behavior of *multiple* team members (see also Marks et al., 2001). The dimension of complexity in organizing team action refers to perceiving or creating opportunities to co-act with others. Simply put, it is relevant in relation to the question, "Can I attain a current action goal by myself?" When the answer is no, this dimension of action organization becomes relevant. Let us assume a team is in possession of the ball and striving to position itself to attempt to shoot. The ball carrier brings the ball down the wing. He monitors the situation for potential pass receivers because he plans to play a cross to bring the ball closer to the goal. At the same time, some players are running to position themselves in the box. They have seen the ball carrier and anticipate an opportunity to complement his efforts. This must occur simultaneously with the person who has the ball looking for a position from which he can play a cross-court pass. Another example is a through ball, in which case the intended receiver of a pass should be underway by the time the ball is kicked to the future point of reception.

We argue that the monitoring of the situational game context in regard to these three dimensions is part of a subjective, constructive process that enables interpersonally coordinated team behavior in situations with no shared mental models and no or no unambiguous affordances.

Mental Representations in the Specification of Situational Context

When monitoring the situational game context, athletes may need to rely on mental models (internal information). Numerous examples of mental models assumed to be relevant in the domain of team sports have been provided: plans and patterns of coordination (Eccles and Tenenbaum, 2004, 2007; Macquet, 2009; Macquet and Kragba, 2015), specific behavioral programs, scripts (Schank and Abelson, 1977), and mental models about other team members (Annett, 1996; Rentsch and Davenport, 2006; Gershgoren et al., 2013), to name only a few (Rouse et al., 1992; Reimer et al., 2006; see also Eccles and Groth, 2007).

To illustrate the contribution of mental models to the monitoring of the situational game context and the subjective construction of opportunities to act, we will consider mental models about other team members. Such mental models have been defined as consisting of, among other things, knowledge about the specific strengths and weaknesses of other team members (Annett, 1996; Reimer et al., 2006; Rentsch and Davenport, 2006; Gershgoren et al., 2013). In team sports, team members are part of the situational game context and represent perceivable external information. An athlete's mental models, MEMBER A and MEMBER B, of her Team Members A and B enable the inclusion of additional information in the situational game context. The mental models themselves need not include other situational factors. While such mental models are restricted in terms of content, they are useful in various game contexts because they are flexibly transferable to various situations and can be combined with other mental models (Macquet, 2009; Macquet and Kragba, 2015). If the mental model MEMBER A includes information about the excellent technical skills of Team Member A, then Team Member A will be considered a potential pass receiver in numerous game situations (Johnson, 2006). Team Member A's status as a potential passing opportunity is thus characterized by a certain level of stability. However, this status is not a permanent attribute of Team Member A. Instead, it also depends on other situational features. If Team Member A is being defended well, the extent to which she represents a passing opportunity requires reappraisal, considering both her abilities (included in MEMBER A) and her current defensive coverage (information provided by the situational game context). In combination, these various sources of information determine a team member's current state as a passing opportunity. According to representational theories of the mind, team members can combine a large but finite number of mental models in numerous ways to create increasingly complex mental models (Margolis and Laurence, 2007). Similarly, we propose that mental models can be combined with external information sources in numerous ways to specify the constraints and opportunities within increasingly complex game contexts. Thus, opportunities to act may be detectable because of the highly elaborate mental model that agents hold of the current situational game context (e.g., a specified team plan to be followed in the given situation). However, athletes may also detect opportunities to act when localizing specific information sources that appear as subcomponents of a complex situational game context (e.g., a team member standing open).

Referring to the great importance Cranach et al. (1986) placed on the above-mentioned structures in understanding interpersonally coordinated team behavior, Seiler (2014) categorizes mental models according to their relatedness to task structure(s), team structure(s), intrateam communication and cooperation. In our example, we will adopt this proposal. We want to stress that the content assigned to one of these four structures is not always clear-cut and that the categories are by no means terminal.

Mental models that relate to task structure can include the macro-environment of a specific sport. This term refers to the general framework provided by the rules of the sport (Kaminski, 2009). Athletes must constrain their actions to this specific framework. Mental models that are linked to individual and role-specific tasks have much in common with the concept of taskwork knowledge (McIntyre and Salas, 1995).

Mental models that relate to group structure may include the positioning and strategic alignment of team members, formal role assignments, roles that are established by means of team members' task-relevant strengths and weaknesses and informal roles (e.g., Annett, 1996; Eccles and Tenenbaum, 2004; Rentsch and Davenport, 2006; Gershgoren et al., 2013).

Mental models related to team communication may refer to communicative signs that announce specific plays. They may also include hand signals indicating a player's availability to receive a pass. Teams often use dedicated signs to inform one another about planned moves (Eccles, 2010; Macquet and Kragba, 2015). Because communication in interactive team sports is often visible to all, attempts to conceal information from the opponent include special communication systems and signs. Team members with a common history in sports may have developed mental models of one another's behavioral idiosyncrasies. This helps players to "read" their team members by using nonverbal channels of communication (e.g., Eccles and Tenenbaum, 2004).

Mental models related to interpersonal coordination have much in common with the concept of teamwork knowledge (McIntyre and Salas, 1995; Bowers et al., 1997; Eccles and Tenenbaum, 2004). These models include information about how the actions of multiple individuals can be successfully integrated to produce group-level performance. Overall team tactics, game plans and scripts for specific situational game contexts are examples of this (Rentsch and Davenport, 2006). These models can also refer to plans with various levels of detail (Eccles and Tenenbaum, 2007). They may be taught explicitly (e.g., through coaching) or developed based on experience in real game situations (Annett, 1996; Eccles, 2010).

AN EXAMPLE FROM BASKETBALL

Figure 1 exemplifies the involvement of mental models in the subjective specification of the situational game context. The scenes present an offensive situation in basketball. They include three chronologically ordered frames that illustrate the evolving game. The three frames highlighted in gray illustrate the game situation as it objectively presents itself to the observer. The figure further includes four levels that indicate the mental models involved in the constructive organization of the situational game context. These levels refer to mental models of the task structure, team structure, communication and coordination. The example illustrates how such models could be involved in specifying information from the situational game context and organizing the situation to reveal opportunities for interpersonally coordinated team behavior. It further shows how situation-related mental models (internal information) and perceptual or communicational (external) information can be integrated according to the hierarchical, sequential and complex dimensions of action organization.

In the initial frame, all athletes have taken their positions, as defined by the team's formation (this refers to the feed-forward function of shared mental models). The offensive team is shown in black, and the defense is shown in white. In basketball, the primary goal of the team in possession of the ball is to score baskets (a). All team members share this group goal and use it to direct their behavior on a global level (e.g., Reimer et al., 2006; Wieber et al., 2012). The point guard (Black #1) is in possession of the ball. Situational constraints prevent him from attaining the primary task goal directly. Often, these constraints are created by opponents who attempt to neutralize the goal-directed efforts of their adversaries. In the current example, the tight defense created by the guard's direct opponent (White #1) does not allow a promising attempt at a long-distance shot. Moreover, three other opponents (White #2, #3, #4) are ready to back up Defender 1 if the point guard attempts to get past him and penetrate into the zone (b). Preparatory steps are required to approximate the hierarchically higher goal sequentially. The team's behavior is directed toward scoring a basket, but in this case, it is adapted to the situational constraints and (re-)organized in a hierarchic and sequential order.

Guided by the newly adopted approximation goal of preparing a shooting possibility for the team, the situation offers the guard three options in terms of passing the ball to a team member (c, d and e). All three options could potentially lead to scoring a basket. This indicates the task situation's equifinality. In choosing one option, mental models about the other team players come into play (f and g). The point guard knows that both the shooting guard (Black #2) and the small forward (Black #3) have high field goal percentage from behind the three-point line. Based on his knowledge about his team members, no option emerges as being superior to the other. Passing the ball to either of them will enable an equally good goal approximation. The shooting guard's defender (White #2) is located at the high post. This leaves enough room for a direct pass to the shooting guard. The shooting guard's skills, in combination with the loose defense of his opponent, become integrated into a contextual opportunity to pass him the ball. Simultaneously, the center (Black #5) takes his position and calls for the ball by raising his arm (h). Passing the ball to the center directly is not an option, because of the long distance involved, combined with a bad passing angle. Instead, delivering the ball to the center via the shooting guard is more favorable. In the current situation, the right side of the playing field offers the point guard better options to act in a goal-directed manner (i and j).

In the second frame, the point guard directs his behavior toward moving the ball to the right side. The shooting guard does not reciprocate the point guard's eye contact (k). This perceptual information warns the point guard that a pass might reach the

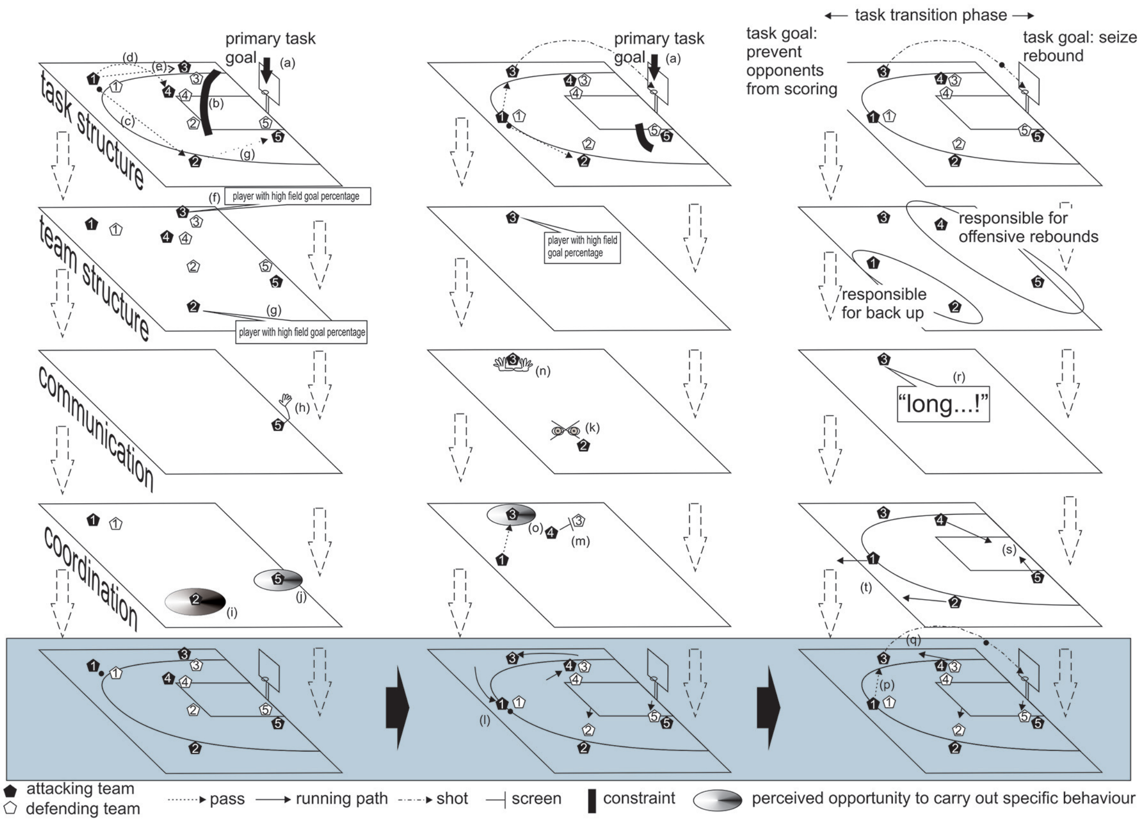

FIGURE 1 | Three-frame sequence of an evolving basketball game situation. Annotations in the text.

shooting guard unexpectedly and thus be risky (e.g., Macquet and Kragba, 2015). Hence, the point guard starts to dribble the ball toward the shooting guard (k). The point guard's defender (White #1) follows closely and still does not allow the shooting guard to shoot the ball or penetrate into the zone. As in the first frame, the search for indirect paths to the primary goal remains necessary. The actions and reactions of the various players cause local changes in the task constraints. As the guard moves toward the right side of the playing field, the defenders of the shooting guard and the center (White #2 and #5, respectively) decrease their distances from their direct opponents. They do so to make passes from the point guard to their directly opposing players more difficult. As a consequence, the previous opportunities to pass (i and j) become less likely to lead to achieving the task goal. Meanwhile, the power forward (Black #4) has set a screen (m) for the athlete defending the small forward (White #3). This screen is not part of a predefined play calling for specific action by the whole team. However, it is a behavior module that can be flexibly adapted to many game situations. Once initiated, those who perceive it understand the steps of the behavior module. The small forward (Black #3) has recognized the opportunity created and taken it to put some distance between himself and his defender. He runs away from the zone to take a position behind the three-point line. He signals his readiness to receive the ball by putting out his hands toward the point guard (n). The point guard perceives the open team member as a passing affordance (o).

In the third frame, the point guard plays the corresponding pass (p). Immediately after receiving the ball, the small forward (Black #3) takes a jump shot (q). As the ball leaves the small forward's hands, a task transition begins. For a short time, the team task is undefined at the level of the primary task goal. If the ball falls into the basket, the primary task goal changes from scoring a basket to preventing the opponents from scoring a basket. If, however, the attempt is not successful, then there may be a chance to regain possession of the ball via offensive rebounding. By calling out that his shot will be off-target (r), the small forward informs his teammates that there will be an opportunity for an offensive rebound. The team's predetermined, shared strategy mandates that both the power forward (Black #4) and the center (Black #5) go for the offensive rebound (s), while the guard and the small forward will run back up the floor to prevent a fast break (t).

This three-frame sequence depicts a short excerpt of a basketball game. It illustrates how mental models shared by the entire team feed forward into behavioral guidelines; this refers to a top-down process. At the same time, it illustrates how information from the situational game context is used to detect opportunities to carry out specific behaviors and thus help to regulate and coordinate team behavior in the process. The pass from the point guard to the open small forward (o) was triggered by the perception of a passing affordance; this is a bottom-up process. The sequence further illustrates how mental models (internal information), in interaction with (external) information sources, enable the assignment of subjective meanings to the situational game context in a modular and constructive manner.

The involvement of mental models in specifying subjective opportunities to (inter)act has primarily been illustrated from the perspective of the point guard (Black #1) and the small forward (Black #3). We suppose that the same process of subjectively specifying a situational game context takes place for all team members. According to this view, interpersonal coordination is enabled when multiple subjective perspectives on the situational game context are constructed congruently, complementarily or reactively (e.g., Eccles and Tenenbaum, 2004; Rentsch and Davenport, 2006; Bourbousson et al., 2011). An example of congruency is the common adoption of the same goals or subgoals, which provides overall direction for personal behavior. An example of reactive complementarity can be seen in the small forward taking advantage of the screen the power forward has set. He reacts to the overt behavior of his team member, which signals the initiation of a specific module of a coordinated team play (give-and-go), and adapts his own behavior to it (Macquet and Kragba, 2015).

In the chosen example, the point guard and small forward do not share the same plans to guide their behavior from Frame 1 through Frame 3. While the entire team shares the same primary goal, the pass from the point guard to the small forward is an example of team coordination being established locally, without the entire team sharing a mental model of the current game situation (see Bourbousson et al., 2012). The situation is characteristically different after the shooting attempt. Now, all team members adapt their behavior to a shared mental plan because everyone assumes their roles as defined by the game strategy for this kind of situation. This example illustrates interpersonal coordination as it is based on the goal-directed adaptation of multiple individuals to situational game contexts. It exemplifies how top-down, bottom-up, and constructivist regulation mechanisms are all involved in this process.

CONCLUDING REMARKS

Interpersonal coordination in interactive sports is a complex phenomenon. Several streams of research approach it from different perspectives. The present article builds on the important contributions some of these approaches have made and aims to integrate and position them within a theoretical framework. This framework borrows from the theoretical outline of group action proposed by Cranach et al. (1986). According to this outline, group behavior regulated by shared team plans is an example of team behavior being directed from the top down via a team-level construct. Team behavior that emerges from athletes perceiving situational affordances is an example of how group behavior is reactive to the situational game context and is thus regulated from the bottom up. We extend the framework by integrating a perspective on the subjective construction of the situational game context. This constructivist perspective accounts for interpersonal coordination as it may be established in novel situations, for which teams do not share mental models. It further accounts for interpersonal coordination in situations with multiple perceived affordances or situations to which athletes are not sufficiently attuned in order to act based on perceived affordances. We argue that under such circumstances, opportunities for interpersonally coordinated team behavior are constructed based on the hierarchical, sequential and complex dimensions of group action organization. We further illustrate how mental models may be involved in this constructive process. For illustrative purposes, we have categorized mental models according to the four structures presented by Cranach et al. (1986). This categorization's primary purpose is to delineate the dynamic integration of multiple mental models as they connect with a given game situation. We want to stress that the categories are exemplary. Finally, an example illustrates how top-down, bottom-up and constructivist processes may simultaneously enable interpersonal coordination.

The integrative perspective's primary implication for research is that a search for *the* one regulation mechanism in the coordination of sports teams is not productive. It argues for following various approaches to better understand the coordination of interpersonal behavior. Provided that multiple mechanisms are involved in enabling interpersonal coordination, one general implication for research is the need to understand in what situations and to what degree they are involved. Hence, designs that estimate the mechanisms' relative contributions to interpersonal coordination in various game contexts are needed.

In our basketball example, the point guard's consideration to pass the ball to the shooting guard is based on both information provided by the situational game context (the shooting guard standing open) and his mental model of the shooting guard's shooting skills. When studying basketballers' real-world behavior, every team member without the ball (all representing potential passing opportunities) can be described by his relative position on the playing field. Perceptual information as available from the subjective perspective of the ball carrier can be quantified (e.g., Steiner and Kunz, 2017). Furthermore, each team member can be assigned values that indicate aspects of the ball carrier's mental models about these particular team members. For example, a high value could indicate that the ball carrier's mental model of this team members is one of a highly skilled shooter. Finally, each team member can be described in terms of the passing priority he is given by a team's playing strategy for this kind of situation. Coding passes dichotomously (the player receiving the balls is coded "1," and all disregarded team members are coded "0"), the effects of the variables representing the information provided by the situational game context, mental models about other team members and shared team strategies can be estimated using logistic regression analyses (e.g., Steiner and Kunz, 2017).

Similar tests could be conducted using experimental designs. In virtual reality settings, the space available to the shooting guard can be manipulated (e.g., Correia et al., 2012). The skill-level of the player in the shooting guard position can be manipulated by showing team members with different levels of shooting ability. Finally, this manipulation can be performed in situations for which teams do and do not have predefined team strategies. Using three gradations for both available space and shooting skills, the experimental manipulation results in a 3 × 3 × 2 design to test the relative effects of available space (information provided by the situational game context), shooting skills (mental models about other team members) and shared team strategies.

Based on our integrative perspective, we hypothesize that passing decisions are affected by the spatial properties of the situational game context, athletes' mental models of team members and shared team plans. Testing each effect in isolation, we thus expect to find higher probabilities for passes to spatially less constrained team members, higher probabilities for passes to team members who are mentally represented as having better shooting skills, and higher probabilities for passes that are in accord with pre-defined team plans. When testing the effects simultaneously, we would, for example, expect larger effects on the part of spatial constraints on passing decisions when no team plans are available than when team plans are available. Furthermore, we expect that the effect of prioritizing passes to more-skilled team members will decrease as passes to more-skilled members become spatially constrained.

With regard to practical applications, the integrative perspective implies that there are multiple paths to interpersonal coordination. According to the provided perspective, shared team plans and strategies are an important pillar of interpersonal coordination. Coaches should enable this kind of pre-process coordination. The fact that it will not be possible to pre-define shared team plans for every kind of situation encountered does not lower their importance in all those situations for which they can be established. A second implication is that coaches should tell their athletes that there will be situations for which no pre-defined team plans are available. Preparing athletes for this kind of unpreparedness could include instructing them to look for the specific opportunities available in given situations (rather than losing time attempting to remember a non-existent plan). A third implication is the need to clearly communicate team goals. According to the organizing rules discussed, primary goals help athletes integrate the available information sources to make sense of the situational game context. Clarifying team goals enables a common denominator in this subjective organization of situational game contexts. Whether the team goal is to play aggressively or to play safely makes a difference in regard to the athletes' perspective on the game. Finally, the framework posits that athletes profit from the information they are given prior to the game. The information could include the specific strengths, prioritized running paths or defensive weaknesses of opponents. This information enables mental models athletes can associate with external information in real time to actively construct their perspective on the situational game context.

To conclude, we have examined the integrative perspective in relation to recent investigations on briefing and debriefing in elite sports. According to Macquet et al. (submitted), head coaches prepare their players by transmitting the game plan to them and providing them with information about their opponents (i.e., strengths, weaknesses, behavioral tendencies, and specific opponents to survey). This information enables team members to share team plans and establish knowledge that can be used to flexibly construct a subjective perspective on the situational game context during the course of the game. Furthermore, coaches teach team-sport players what to look for (Macquet et al., 2015). They guide the players' perceptions and enable them to perceive meaningful information. This guidance helps players read the game and better coordinate with their teammates and opponents. In our view, these findings support the presented integrative perspective. They indicate that the integrative perspective may represent a greater challenge to empirical science than to applied work. Research attempts to describe and explain the principles underlying interpersonal coordination via scientific means. This includes various approaches that may not always enable a common perspective on the phenomenon in question. In our integrative perspective, these various approaches do not strive for exclusiveness or general superiority. Combined, they contribute to a better understanding of a common focus: interpersonal coordination within interactive team sports.

AUTHOR CONTRIBUTIONS

SS, AM, and RS drafted the work and provided approval for the version to be published.

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Team Resilience as a Second-Order Emergent State: A Theoretical Model and Research Directions

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Resilience has been recognized as an important phenomenon for understanding how individuals overcome difficult situations. However, it is not only individuals who face difficulties; it is not uncommon for teams to experience adversity. When they do, they must be able to overcome these challenges without performance decrements.This manuscript represents a theoretical model that might be helpful in conceptualizing this important construct. Specifically, it describes team resilience as a second-order emergent state. We also include research propositions that follow from the model.

Keywords: team performance, resilience (psychology), stress, psychological, team processes, team training

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INTRODUCTION

In 1914, Sir Ernest Shackleton and his team set out from Plymouth, England on a quest to walk across the Antarctic continent. The goal was to be the first person to successfully cross the 1,500 miles of frozen tundra. Upon stopping at a whaling station as they set out on their quest, the team found itself stuck on ice. They spent nearly 11 months by the ice-bound ship, until the ice crushed it, eventually causing it to sink. After spending a week rowing in lifeboats, the team arrived at Elephant Island. The small island offered no protection or resources. Shackelton strategized, and devised a small subset of his team members to travel 800 miles back to the whaling station they previously left in order to seek help. After rowing for 17 days, they arrived, only to realize they were on the wrong side of the island. Approximately 22 miles of ice and mountains stood them and the whaling station. However, they managed to make it to their destination in 36 h. Given the ice and storms, it took Shackleton nearly 3 months to rescue the remaining men on Elephant Island. More than 2 years after leaving Plymouth port, all of the men had finally returned. The story of Shackleton story is so compelling due to the resilience he and his team members displayed. While it took more than 2 years, everyone returned home safely due to the resilience displayed by Shackleton and his team.

WHY IS TEAM RESILIENCE IMPORTANT?

Resilience has been recognized as an important phenomenon for understanding how individuals overcome difficult situations (Masten and Osofsky, 2010). However, it is not only individuals who face difficulties; it is not uncommon for teams to experience adversity. When they do, they must be able to overcome these challenges without performance decrements. Indeed, research has identified a multitude of stressors that teams often face, including: poor interaction quality, poor communication channels, lack of back-up behavior, and negative organizational culture. While these stressors have been identified, the exploration of how teams can utilize their collective resources to overcome them has been largely overlooked. However, focus on resilience has recently grown, as researchers attempt to identify how teams and groups positively adapt to adversity (West et al., 2009; Bennett et al., 2010; Morgan et al., 2013, 2015; Alliger et al., 2015). It appears as though team resilience is a critical team level capacity that facilitates the rebound of teams after an adverse event. In light of this definition of resilience as a capacity, resilience can be seen as a buildable capacity. Teams that thrive, rebound, or positively adapt to adversity are more unlikely to experience the deleterious effects of challenging situations.

DEFINITIONS OF RESILIENCE

The term *resilience* comes from the Latin word "resiliere," which means to "bounce back"; it typically refers to the ability to recover or rebound after a setback (Fletcher and Sarkar, 2012). Indeed, the concept of resilience has been deemed an important phenomenon for understanding how successful adaptation occurs following an unanticipated—often negative—event (Wright and Masten, 2015). Interest in studying resilience as a coping or adaptation mechanism has increased rapidly over the last 20 years, and is considered across a variety of contexts, such as communities (Brennan, 2008), teams (Pollock et al., 2003), education (Gu and Day, 2007), organizations (Riolli and Savicki, 2003), military (Palmer, 2008), and athletic performance (Galli and Vealey, 2008).

As interest in resilience rises, a number of definitions and conceptualizations have been put forth in the literature. Not surprisingly, one of the primary shortcomings of previous resilience research is the wide discrepancy regarding its definition and conceptualization (Fletcher and Sarkar, 2012). More specifically, resilience has been referred to sometimes as a trait, other times as a process, and yet other times as an outcome. Davydov et al. (2010) assert that these discrepancies and definitional confusion have hindered the evaluation and validity of resilience research findings. To complicate matters further, resilience has been studied at different levels of analysis. Traditionally, resilience has been used to refer to individuals, but more recently has been applied to teams and organizations. The sections that follow define resilience as it has been used at these various levels.

RESILIENCE AS A PROCESS

Resilience researchers have shifted to examining resilience as a dynamic process, rather than an enduring trait. As a fluid process, some have proposed that resilience gradually develops over time, through interactions between the individual and the environment (Egeland et al., 1993). Most scholars agree that within the process, there is a complex interaction of multiple factors that determines whether resilience is demonstrated.

In line with the notion of resilience as a process, Galli and Vealey (2008) found that a significant facet is *agitation*, a process in which unpleasant emotions or mental struggles are countered through various coping strategies. Notably, positive adaptation occurs gradually, and requires frequent shifts of thought. These findings can be nested within the context of contemporary stress and emotion theory, which suggests that individuals construe relational meanings based on their interactions in a given environment (Lazarus, 1998). Similarly, a recent theoretical model offering insight into resilience is the "Meta-Model of Stress, Emotions, and Performance" (Richardson, 2002). The model suggests that suggests that stressors are created in the environment, become mediated by perception, appraisal, attribution, and coping, and finally, result in adaptive or maladaptive stress responses. The relationship between these processes and responses are further moderated by situational and individual level characteristics, including self-esteem, positive affect, and self-efficacy (Schaubroeck et al., 1992; Ganster and Schaubroeck, 1995; Schaubroeck and Merritt, 1997). These characteristics affect stress processes at several points, including stressor appraisal, meta-cognition in response to affect, and coping strategy selection.

Other researchers have also emphasized the role of stressors in the development of team resilience. For example, Meneghel et al. (2016) emphasize the role of job demands in the development of team resilience. However, their data indicate that there is a more complex relationship between job demands, resources, resilience, and performance than one might expect. More specifically, job demands may induce stress and thereby hamper positive emotions, thereby decreasing team resilience. However, when job demands do not place too much workload on team members, this may lead to a sense of accomplishment, thereby inducing positive emotion and the facilitation of resilience.

In his work, Richardson (2002) defines resilience as "the process of coping with stressors, adversity, change or opportunity in a manner that results in the identification, fortification, and enrichment of resilient qualities or protective factors" (p. 308). According to the theory, the process of resilience begins at the state of "biopsychospiritual homeostasis" (i.e., a comfort zone), in which an individual is physically, mentally, and spiritually in balance. This state is disrupted if an individual does not have sufficient protective factors to buffer strains, stresses, or adverse events. Over time, an individual will adjust and begin the process of reintegration. The reintegration process results in one of four outcomes: (1) resilient reintegration (additional protective factors are attained or strengthened, and homeostasis is once again achieved) (2) homeostatic reintegration (an individual remains in homeostasis, just "getting past" the situation), (3) reintegration with loss (protective factors are lost, and a lower level of homeostasis is achieved), or (4) dysfunctional reintegration (individuals resort to destructive behaviors) (Richardson, 2002).

Morgan and his colleagues point out that team resilience also has elements of a developmental process (Morgan et al., 2015). They conducted a narrative analysis of world-class rugby players. The results of this analysis suggest that team resilience might be developed during different phases of the team's development. For example, early development of resilience might be characterized by behaviors designed to increase collective efficacy. However, more mature teams focused on dealing with failures.

As previously noted, the notion of resilience as a process has also been well-developed at the organizational level. According to this body of work, resilient organizations treat deviations from boundary conditions indicators of overall system health. Resilient organizations behave as high reliability organizations (HROs). These organizations overcome adversity with few to no errors due to their "intelligent wariness" (Reason, 2000) and a "preoccupation with failure" (Weick and Sutcliffe, 2006). Resilient organizations intentionally test their risk assumptions and assumptions regarding overall system health (Weick and Sutcliffe, 2006). Furthermore, highly resilient organizations empower their employees to speak up to report errors or conditions that could foster errors. These organizations recognize that speaking up is critical, even if production is halted to mitigate a foreseeable potential error. Moreover, resilient organizations believe they have the capability to cope with a plethora of stressors, and continuously strive to strengthen their resources to do so. Therefore, resilient organizations acknowledge that they are imperfect, but believe they can grow by learning from near events and actual events (Woods, 2006). While this work has been conducted at the organizational (rather than team) level, given that this is the most well-developed area of resilience research, we believe this work can be translated into lessons for building team resilience. For example, given that resilient organizations encourage speaking up to report errors and are capable of handling high amounts of stress, incorporating techniques to encourage communication and cope with stress into team training may be key to facilitating resilience at the team level.

Resilience also requires practices that facilitate competence, and encourage growth to buffer against jolts and strains (Vogus and Sutcliffe, 2007). Such capabilities facilitate resilience by expanding informational inputs, creating flexibility, and reconfiguring resources. Teams have the ability to continuously grow and refine their capabilities, which in turns allow them to have greater predictive abilities, remain flexible, and buffer the detrimental effects typically associated with unexpected or negative events.

The resilience mechanisms outlined above result from and encourage a unique way of "seeing." Organizations that are resilient are more likely to be composed of teams that are capable of elucidating weak signals through the monitoring of current operations. As such, these teams are better equipped to identify weak signals because of their highly developed response capabilities, which allow them to respond more adaptively to a great array of events. Moreover, given their superior information processing systems and management, disruptive or negative events are treated as opportunities as opposed to threats (Jackson and Dutton, 1988; Barnett and Pratt, 2000). For example, teams in HROs use "near misses" to assess the overall functioning of the system and view them as opportunities for learning (Weick and Sutcliffe, 2006).

Moreover, *teams* in resilient organization tend to engage in mindful organizing (Weick et al., 2008). This entails the ongoing development and refinement of a shared understanding of problems faced by the organization and the resources and capabilities available to maintain safe performance. Vogus and Sutcliffe (2012) suggest that mindful organizing is the result of five processes: (1) assessment of possible and extant system risks, (2) questioning of previous assumptions, (3) discussion of individual, team, and organizational resources and abilities, (4) collective learning following an adverse event, and (5) deference to expertise. When employees engage in these processes, organizations are better equipped to identify errors in a timely manner, thereby minimizing detrimental outcomes.

Conceptualizing resilience as a dynamic process allows scientists to create hypotheses about the conditions and behaviors that lead to resilience. Viewing resilience as a process may be useful, as process theories "often deal with the evolution of relationships between individuals or team members, or with the cognitions and emotions of individuals as they interpret and react to events" (Langley, 1999, p. 693). As such, process theories often involve a plethora of quantitative and qualitative information. Although this can make interpretation and analysis quite difficult and complex (Langley, 1999), taking a process view allows us to more precisely parse out the components, events, and relationships underlying resilience.

TEAM RESILIENCE AS AN EMERGENT STATE

Many team researchers have tended to focus on the construct of adaptability—in particular task adaptability (i.e., the ability to shift strategies in response to changing situational or task demands)—but these treatments may not capture the essence of resilience. Recently however, the notion that resilience is best considered an *emergent state* has been proposed (Maynard and Kennedy, 2016). The term emergent state was proposed by Marks et al. (2001) to describe certain types of team phenomena that were not actual processes (although they had been treated as such in prior work). According to Marks et al. (2001), "Emergent states describe cognitive, motivational, and affective *states* of teams, as opposed to the nature of their member interaction. Although researchers have not typically classified them as such, emergent states can be considered both team inputs and proximal outcomes. For example, teams with low cohesion (an emergent state) may be less willing to manage existing conflict (the process), which, in turn, may create additional conflict that lowers cohesion levels even further" (p. 357). The authors go on to clarify that emergent states are not actual team actions or interactions; rather, they should be viewed as an outcome of team experiences, including team processes.

Maynard and Kennedy (2016) view team resilience as an emergent state, given the idea that resilience is dynamic (Luthar et al., 2000) and is impacted by adaptation (among other team processes) (Moran and Tame, 2012). Reich et al. (2010) purport that resilience is the result of adaptation to difficulty, which is in line with the notion of team resilience as an emergent state. Similarly, conceptualizing resilience as an emergent state is in line with work that has defined it as "a team's belief that it can absorb and cope with strain, as well as a team's capacity to cope, recover and adjust positively to difficulties" (Carmeli et al., 2013, p. 149).

The manner by which various states emerge has been well-articulated in the context of team learning by Kozlowski and Bell (2008). Kozlowski and Bell (2008) suggest three central tenets of team learning. First, it is unquestionable that learning occurs within individuals. Next, while learning can occur at the individual-level, team learning occurs in a task and social context that shapes how learning occurs and what is learned. Finally, team learning is a dynamic process, occurring over repeated interactions over time, resulting in emergent outcomes suggesting that learning has taken place.

The value of the emergent state construct has been demonstrated empirically in recent team research. For example, Jehn and colleagues recently demonstrated that certain emergent states mediated the relationship between conflict and team performance (Jehn et al., 2008). Similar results were obtained by Bradley et al. (2012).

Employing Marks et al.'s (2001) definition, Maynard and Kennedy (2016) incorporated the concept of team resilience as an emergent state in a model of team adaptation. According to these authors, "the construct of resilience (at both the individual and team-level of analysis) has been viewed as a trait, a process, and as an outcome" (p. 8). They concluded, however, that team resilience is best thought of as an emergent state in the manner described by Marks et al. (2001). Team resilience as an emergent state suggests underlying dynamic properties that may shift as a result of team-level inputs, context, processes, and outcomes.

A similar position has been articulated by Sharma and Sharma (2016). These researchers sought to develop a measure of team resilience. A result of their scale development work was a model in which team resilience is a consequent of various latent variables comprised by more specific behaviors. While they did not invoke the construct of emergent states, their resulting model implies a multi-level process in the development of team resilience.

Our conclusion is similar: resilience is the result of a dynamic process that effects and is affected by other salient team variables. In fact, we argue that team resilience may be a "second-order"emergent state; that is an emergent state that is actually the result of other emergent states in the team. Indeed, team resilience may mediate the relationship between other team emergent states and outcomes during times of stress.

INDIVIDUAL RESILIENCE

In regard to inputs at the individual level, there is growing research regarding how individual member qualities influence team adaptability (LePine, 2003, 2005). As an example, LePine (2005) revealed an interaction between the difficulty of a goal, and learning orientation. Teams that had difficult goals that consisted of team members with a learning orientation had higher rates of adaptation. As suggested by Maynard and Kennedy (2016) "We can envision more work at the team-level of analysis leveraging such individual-level work by either aggregating such individual-level constructs or by examining upward influence-type models (e.g., Mathieu and Taylor, 2007)" (p. 22).

Despite increased interest in resilience, there remains definitional debate regarding what exactly it means to be a resilient individual. More specifically, it is yet unclear whether resilient individuals thrive (i.e., grow beyond baseline functioning) or more simply adapt and return to baseline functioning after facing a setback. In line with the latter idea, Masten et al. (1990) define resilience as "The process of, capacity for, or outcome of adaptation despite challenging or threatening circumstances" (p. 426). Similarly, Lee and Cranford (2008) define resilience as "The capacity of individuals to cope successfully with significant change, adversity, or risk" (p. 213). However, other authors purport that resilience goes beyond adaptation to adversity. For example, Leipold and Greve (2009) define resilience as "An individual's stability or quick recovery (or even growth) under significant adverse conditions" (p. 41). Moreover, Connor and Davidson (2003) suggest that resilience is "The personal qualities that enables one to thrive in the face of adversity" (p. 76).

Despite this uncertainty, Fletcher and Sarkar (2013) pointed out that definitions of resilience are typically founded upon two fundamental notions: adversity and positive adaptation. In fact, researchers generally agree that positive adaption to adversity must be evident in order for resilience to be demonstrated. Luthar and Cicchetti (2000) asserted further that *adversity* "typically encompasses negative circumstances that are known to be statistically associated with adjustment difficulties" (p. 858). In addition, according to Davydov et al. (2010), the mechanisms underlying resilience vary, ranging from mild adversity (e.g., stress at work) to strong adversity (e.g., bereavement). Regarding the second underlying concept, positive adaptation "may be likened to a springboard that propels the survivor to a higher level of functioning than that which they held previously" (Linley and Joseph, 2004, p. 602). In line with this definition, positive adaptation therefore represents a gain following the adverse event, as opposed to recovery from the loss or homeostatic return to baseline.

Others (e.g., Luthar et al., 2000) suggest that positive adaptation simply refers to the ability to meet the demands faced during adversity. Furthermore, others assert that positive adaptation may be a combination of the previous definitions; Leipold and Greve (2009) suggest that positive adaptation refers to "An individual's stability or quick recovery (*or* even growth) under significant adverse conditions" (p. 41). Thus, the definitional debate in the resilience literature seems to surround the second core process of adaptation. Luthar and colleagues (Luthar et al., 2000; Luthar, 2006) suggest that positive adaptation may be a function of the severity of the adverse event, and what constitutes positive adaptation might be context specific.

Alongside definitional confusion, there has been considerable debate about the basic conceptualization of resilience. Although all people possess some degree of resilience, not everyone is equal in this regard. While some people have difficulty overcoming commonplace hassles, others react positively in the face of even the most challenging situations (Bonanno, 2004). In search of an explanation for this variance, early resilience researchers sought to identify factors that protect individuals from experiencing adverse effects after a setback. In this regard, resilience can be conceptualized as an amalgamation of protective factors, or traits, that "influence, modify, ameliorate, or alter a person's response to some environmental hazard that predisposes to a maladaptive outcome" (Rutter, 1985, p. 600). This conception was originally suggested by Block and Block (1980), using the term "ego resilience" to reflect traits such as resourcefulness, character, and flexibility. Those high on ego resilience were found to be energetic, optimistic, and had the ability to detach in order to problem solve (Block and Block, 1980). Since the origination of this work, there seems to be general agreement that the construct of resilience implies a protection against future stressors (Fletcher and Sarkar, 2016).

Several specific protective factors have been examined by resilience researchers, including: positive emotions (Tugade and Fredrickson, 2004), hardiness (Bonanno, 2004), self-efficacy (Gu and Day, 2007), extraversion (Campbell-Sills et al., 2006), self-esteem (Kidd and Shahar, 2008), positive affect (Zautra et al., 2005), and spirituality (Bogar and Hulse-Killacky, 2006).

TEAM RESILIENCE

Given the growth of teamwork within organizations, resilience researchers have recently shifted their focus from the individual and community levels to the team level (Norris et al., 2008; Alliger et al., 2015). As recently suggested by Brodsky et al. (2011), "a focus on the individual is not enough" (p. 233). In line with Alliger et al. (2015), we purport that individual and team resilience while related, are distinct constructs. A team comprised of resilient members does not necessarily make the team resilient. At the team level, resilience has been characterized by variables including collective efficacy, creativity, cohesion, social support, and trust (Gittell et al., 2006; Norris et al., 2008; Blatt, 2009). Moreover, teams that encompass a broader perspective in the face of adversity have a greater likelihood of positive adaption (Bennett et al., 2010). In support of the notion that team resilience research is critical, Bennett et al. (2010) purports that, "resilience may be viewed as much a social factor existing in teams as an individual trait" (p. 225). This would suggest that teams have the capacity for positive adaptation through collective interactions, rather than as isolated individuals. As stated by West et al. (2009), "Team resilience may prove to be an important positive team level capacity that aids in the repair and rebound of teams when facing potentially stressful situations. Teams which display the ability to either thrive under high liability situations, improvise and adapt to significant change or stress, or simply recover from a negative experience are less likely to experience the potentially damaging effects of threatening situations" (p. 254).

ORGANIZATIONAL RESILIENCE

As noted by Maynard and Kennedy (2016), research is lacking on the effect of organizational-level inputs on team resilience. Work by Gibson and Birkinshaw (2004) have suggested organizational context to be a pre-cursor to team ambidexterity. More specifically, the more supportive the context, the greater the ambidexterity. Team ambidexterity "allows teams to reconcile the tensions between alignment and adaptability" (Maynard and Kennedy, 2016, p. 12). Moreover, Gibson and Birkinshaw (2004) found that ambidexterity is a mediator between context and unit performance. Thus, the contextual inputs at the organizational level seem to facilitate unit adaptation.

As defined by Vogus and Sutcliffe (2007), resilience at the organizational level refers to the ability to maintain positive adjustment to difficult situations, such that the result is a stronger and more resourceful organization. Since organizations that are resilient as a whole have greater resources, this may allow their individual teams to also be more resilient as they have access to a greater repertoire of resources when faced with a difficult situation. "Difficult situations" include crises, unexpected events, deviations from boundary conditions (i.e., deviations from normal functioning), strains, and emerging risks. It is important to note that the amalgamation of small stresses, deviations, or interruptions can pose a significant risk to system functioning just as readily as a more catastrophic event (Rudolph and Repenning, 2002). Adjustment to adversity at the organizational level has been said to strengthen individual teams through "a hierarchical integration of behavioral systems whereby earlier structures are incorporated into later structures in increasingly complex forms" (Egeland et al., 1993, p. 518). Alternatively stated, resiling from difficult conditions necessitates the activation of latent resources. Therefore, resilience encompasses more than a specific adaption. Competence in the face of one adversity implies a greater likelihood of competence in the face of the next adversity. In order to be resilient, a team must be prepared for hardship, which requires an "improvement in overall capability, i.e., a generalized capacity to investigate, to learn, and to act, without knowing in advance what one will be called to act upon" (Wildavsky, 1991, p. 70). In this light, resilience greatly depends on learning from previous experiences and adversities which facilitates future learning. However, because resilience is independent of learning activities, it represents a greater repertoire of capabilities.

Several resilience processes at the organization level have been identified by Brodsky et al. (2011), which include: a sense of community, positive team culture, reframing of stressors, striving to achieve the organization's mission, shared values, and malleable team structures (Fletcher and Wagstaff, 2009; Wagstaff et al., 2012). This supports the contention of Chan (1998), who suggested that although constructs may fall under the same domain, they manifest differently at different levels (i.e., individual or team). A similar position has been advocated more recently by Morgan et al. (2013).

AN INPUT-MEDIATOR-OUTCOME (IMO) MODEL OF TEAM RESILIENCE

What follows is our attempt to synthesize past work to create a model of team resilience by employing a modified Input-Process-Outcome (I-P-O) framework advocated by Ilgen et al. (2005): the Input-Mediator-Output-Input (I-M-O-I) framework. According to Ilgen et al. traditional I-P-O models failed to account for the dynamic complexity that characterizes team behavior. Using Marks et al.'s (2001) notion of emergent state described above, they substitute the term "mediator" for "process" in the original I-P-O framework. In doing so, these authors contend that it "reflects the broader range of variables that are important mediational influences with explanatory power for explaining variability in team performance and viability," (Ilgen et al., 2005, p. 520). The following sections first summarize past work into the inputs, processes and mediators, and outcomes associated with resilience as the individual, team, and organizational levels. We included the individual levels in our review because they are part of the dynamic system that effects team resilience. Our contention is that it is essential to maintain this multi-level view in order to understand the full complexity of team performance and outcomes. Based on this review, we conclude by offering a comprehensive model of those things that contribute to development of resilience and outcomes that can be expected as a result of achieving resilience. We hope this model will stimulate further thinking and research.

BEGINNING WITH THE END: DEFINING OUTCOMES OF RESILIENCE

To begin specification of an I-M-O model of resilience, we reviewed literature summarizing the outcomes that are expected to result from resilient behavior. Our goal here is to synthesize what has been theorized about the expected outcomes of resilience at the individual, team and organizational levels (see **Table 1**). Implicit in all of these outcomes is that they must occur during a period of stress that is sufficient to interrupt performance.

DEFINING INPUTS OF RESILIENCE

The inputs to resilience vary greatly depending on the level at which it is being considered. **Table 2** summarizes the major inputs that enable resilience, again ordered by whether they occur at the individual, team, or organizational level. At the individual level, inputs to resilient behavior are most often considered to be individual traits. These traits serve to buffer individuals to the effects of a stressor and/or allow him or her to bounce back quickly. At the team level, inputs to resilience are not traits, rather they are factors that exist at the team level. However, they operate in a similar manner to individual inputs in that they can have a buffering effect on the team's experience of stress and/or equip them to cope with the stress. Finally, at the organizational level, input factors are similar to team-level inputs in that they exist at the organizational level and serve to set the stage for coping behaviors by the organization.

PROCESSES ASSOCIATED WITH RESILIENCE

Similar to input factors, the processes associated with resilience behavior vary greatly depending on the level being considered. At the individual level, resilient processes are most often conceived of as adaptive behaviors. At the team and organizational levels, resilient processes are more closely associated with collective behavior by team members. **Table 3** summarizes our review of the literature regarding processes associated with resilience.

TABLE 1 | Expected outcomes of resilience at the individual, team, and organizational levels.

Level	Construct	Definition	Supporting authors
Individual	Psychological health	Decreased prevalence of stress-related diseases such as Post-Traumatic Stress Disorder and Complicated Grief. Alternatively, resilience has also been associated with faster recovery from these diseases if they should occur.	McNally, 2003; Holland et al., 2009; Bonanno and Diminich, 2013
	Physical health	Decreased prevalence of physical disease following stress; increased pain tolerance; improved recovery from illness.	Rutter, 1998; Sturgeon and Zautra, 2013
	Sustained social ability	The ability to maintain effective relationships and demonstrate appropriate social skills in the face of stress.	Criss et al., 2015
	Sustained cognitive ability	The ability to collect, process, and act on information during or following periods of extreme stress.	Shia et al., 2015
Team	Maintenance of performance	Ability to maintain high levels of performance in spite of task challenges or difficulties.	Wilson et al., 2006
	Error avoidance	The prevention and/or minimization of errors.	Shawn Burke et al., 2005
	Desire to remain	Desire by team members to remain as part of the team.	Hackman and Wageman, 2005
Organizational	Maintenance of performance	Ability to maintain high levels of performance in spite of task challenges or difficulties.	Vogus and Sutcliffe, 2007
	Error avoidance	The prevention and/or minimization of errors.	Brown, 2004; Jeffcott et al., 2009
	Desire to remain	The extent to which an individual wishes to remain a member of the organization.	Kim and Aldrich, 2002; Majchrzak et al., 2007
	Sustained results	The ability to duplicate results each time a strategy is implemented.	Averett, 2001; Lissack and Letiche, 2002
	Longevity	Timespan indicative of the organization's success in its business environment in the past.	Linnenluecke and Griffiths, 2010

TABLE 2 | Inputs that enable resilience.

Level	Construct	Definition	Supporting authors
Individual	Optimism	The tendency to anticipate a positive outcome, even in the face of adversity.	Riolli et al., 2002; Karademas, 2006
Individual	Personality	Refers to traits such as openness, agreeableness, emotional stability, and social competence.	Friborg et al., 2005
Individual	Goal orientation	A tendency to validate one's achievement ability in academic or performance settings.	VandeWalle et al., 2001
Individual	Coping flexibility	The ability to flexibly adjust coping strategies to face distinct stressors.	Lam and McBride-Chang, 2007; Galatzer-Levy et al., 2012
Individual	Coping	A dynamic situation-specific reaction to stress.	Lazarus, 1999; Eisenbarth, 2012
Individual	Self-esteem	A positive or negative attitude toward oneself.	Eisenbarth, 2012
Individual	Mental toughness	The ability to persevere through difficult circumstances and emerge without losing confidence.	Reivich et al., 2011
Individual	Directed attention	The ability to direct interpretations to a more flexible disposition.	Loprinzi et al., 2011; Sood et al., 2011
Individual	Cognitive restructuring	The modification of irrational thoughts.	Fava and Tomba, 2009
Individual	Sense of humor	Ability to find humor about life situations and about one's self.	Rutter, 1987; Bobek, 2002; Earvolino-Ramirez, 2007
Individual	Patience	The capacity to accept or tolerate delay, trouble, or suffering.	Connor, 2006
Individual	Faith	A belief in the doctrines of a religion.	Richardson, 2002; Ní Raghallaigh and Gilligan, 2010
Individual	Perseverance	Perceived ability to overcome adverse circumstances.	Floyd, 1996; Rolland and Walsh, 2006
Individual	Self-control	The capability to modulate and control impulses.	Moffitt et al., 2011
Individual	Hardiness	An openness to viewing change as a challenge.	King et al., 1998; Almedom, 2005
Individual	Grit	The passionate pursuit of long-term goals.	Duckworth et al., 2007
Team	Trust	The belief, confidence, or expectation that a fellow team member will be responsive and act in an ethically justifiable manner.	Meredith et al., 2011; Stephens et al., 2013
Team	Explicit communication	The transmission of ideas, knowledge, and thoughts to the receiving party between two or more team members via a verbal channel.	Entin and Serfaty, 1999; Vidal et al., 2009
Team	Implicit communication	The transmission of ideas, knowledge, and thoughts between two or more team members via a nonverbal channel.	Entin and Serfaty, 1999; Paton and Jackson, 2002
Team	Norms	A standard or pattern or behavior that has been established amongst team members.	Morgan et al., 2013
Team	Transactive memory	A combination of knowledge held by individual team members and the collective awareness of individual team member knowledge.	Ilgen et al., 2005
Team	Psychological safety	A perception that one can speak up without repercussion.	Carmeli and Gittell, 2009; Carmeli et al., 2009
Team	Stability of membership	The extent to which team members wish to remain as part of the team.	Kim and Aldrich, 2002; Majchrzak et al., 2007
Team	Assertiveness	The ability of a team member to communicate in a persuasive manner to other team members.	Wilson et al., 2005
Organizational	Preoccupied w/failure	Engagement in the analysis of possible vulnerabilities.	Vogus and Sutcliffe, 2007
Organizational	Agility	The ability to quickly and effectively cope with unexpected changes in the environment.	Lengnick-Hall and Beck, 2009; Fairbanks et al., 2014
Organizational	Monitoring	The ability to discern what is or is likely to become a threat in the near future.	Hollnagel et al., 2014
Organizational	Reluctance to simplify Interpretations	Tendency of an organization to question assumptions.	Vogus and Sutcliffe, 2007
Organizational	Sensitive to operations	A willingness to discuss the capabilities that facilitate safe performance.	Vogus and Sutcliffe, 2007
Organizational	Committed to resilience	The demonstration of effort to collectively learn from errors that have occurred.	Vogus and Sutcliffe, 2007
Organizational	Deference to expertise	The ability to migrate decisions to the person(s) with the greatest expertise for the issue at hand.	Vogus and Sutcliffe, 2007
Organizational	Adaptive capacity	A measure of dynamics of an organization that allows it to make decisions in both daily situations and crisis situations.	McManus et al., 2008; Lengnick-Hall et al., 2011
Organizational	Situation awareness	An understanding of the make-up of the organization and how its components relate to each other.	McManus et al., 2008

TABLE 3 | Review of processes associated with resilience.

Level	Construct	Definition	Supporting authors
Individual	Stress management	A technique aimed at controlling an individual's stress level; particularly chronic stress levels.	Steinhardt and Dolbier, 2008; Loprinzi et al., 2011; Sood et al., 2011
Individual	Relaxation/ Breathing	Techniques designed to reduce the physiological stress response through controlled breathing.	Deckro et al., 2002; Dziegielewski et al., 2004
Individual	Social support	A safe environment where individuals are encouraged to share their thoughts and feelings with others.	Karademas, 2006; Reivich et al., 2011
Individual	Imagery/mental stimulation	The use of all senses to rehearse an event scenario mentally.	Arnetz et al., 2009
Individual	Mindfulness	A mental state in which an individual focuses attention on the present moment, while acknowledging one's feelings, thoughts, and bodily sensations without judgement.	Shapiro et al., 1998
Team	Forceful backup	The questioning of a decision for which contrary evidence can be provided; the verbalization of conflicting information.	Lamb et al., 2014
Team	Planning	Formulation of a preconceived way to deal with hazards, crises, or potentially unexpected adverse event.	Crichton et al., 2009; Lentzos and Rose, 2009
Team	Leadership	The process of a superior influencing subordinates to accomplish team goals.	Lugg and Boyd, 1993; Wing, 2005; Stewart and O'Donnell, 2007
Team	Adaptability	A functional change in response to altered environmental and situational contingencies.	Pulakos et al., 2006; Carmeli et al., 2013; Alliger et al., 2015; Morgan et al., 2015; Wright and Masten, 2015
Team	Compensatory behavior	The ability to step in and provide back-up behavior for team members when they are unable to perform the task independently.	Van Der Haar et al., 2008
Team	Performance monitoring	Team's ability to monitor individual members' and the team's performance.	Wilson et al., 2005
Team	Shared decision making	Decisions are made jointly by team leaders and subordinates.	Stokols et al., 2008
Organizational	Anticipation	Knowing what to expect in terms of developments, threats, and opportunities that may occur in the near future.	Woods, 2006
Organizational	Information sharing	Transmission of data between a sender and receiver.	Paulus and Nijstad, 2003
Organizational	Simulating	Practice of the handling of unlikely events.	Vogus and Sutcliffe, 2007
Organizational	Management of keystone vulnerabilities	Management of organizational aspects are likely to mitigate negative impacts of a crisis.	McManus et al., 2008
Organizational	Information gathering	The process of collecting data and information pertinent to the task.	Kendra and Wachtendorf, 2003; Somers, 2009
Organizational	Layoff avoidance	Retainment of employees.	Gittell et al., 2006
Organizational	Financial reserves	Retainment of financial resources available during a crisis.	Gittell et al., 2006
Organizational	Broad resource networks	Ability to form relationships with others who may share fundamental resources.	Werner and Smith, 2001; Lengnick-Hall et al., 2011
Organizational	Diffused power	Reliance on self-organization for the creation of a holographic structure.	Lengnick-Hall et al., 2011
Organizational	Strategic HR management	Development of the requisite knowledge, skills, abilities, and other abilities (KSAOs).	Lengnick-Hall et al., 2011
Organizational	Enterprise systems	Large-scale packages that support organizational processes and information flows in complex organizations.	Ignatiadis and Nandhakumar, 2007
Organizational	Relational reserves	The maintenance of positive social relationships within the organization.	Gittell et al., 2006

A COMPREHENSIVE MODEL OF TEAM RESILIENCE

Figure 1 displays a summary of the variables included in the tables above. As noted previously, we conceptualize team resilience as a second *order mediator*. That is, team resilience is best thought of as enabled by a combination of other team emergent states including cohesion, collective efficacy, culture, shared mental models, familiarity, and adaptability (see **Table 4**). Our conclusion is based on the notion that resilience is the result of these other states and it enables the team to achieve either positive or negative outcomes. It is this quality of resilience that is unique in that it can act as a buffer for negative outcomes and also as an enabler of positive ones.

Inspection of the model in **Figure 2** reflects what we have discussed above. According to this model, team resilience is a second order emergent state that is situated between other team emergent states (see **Figure 1**) and outcomes (see **Figure 1**). Team emergent states are the result of various team processes (see **Figure 1**) and those, in turn, are driven by input

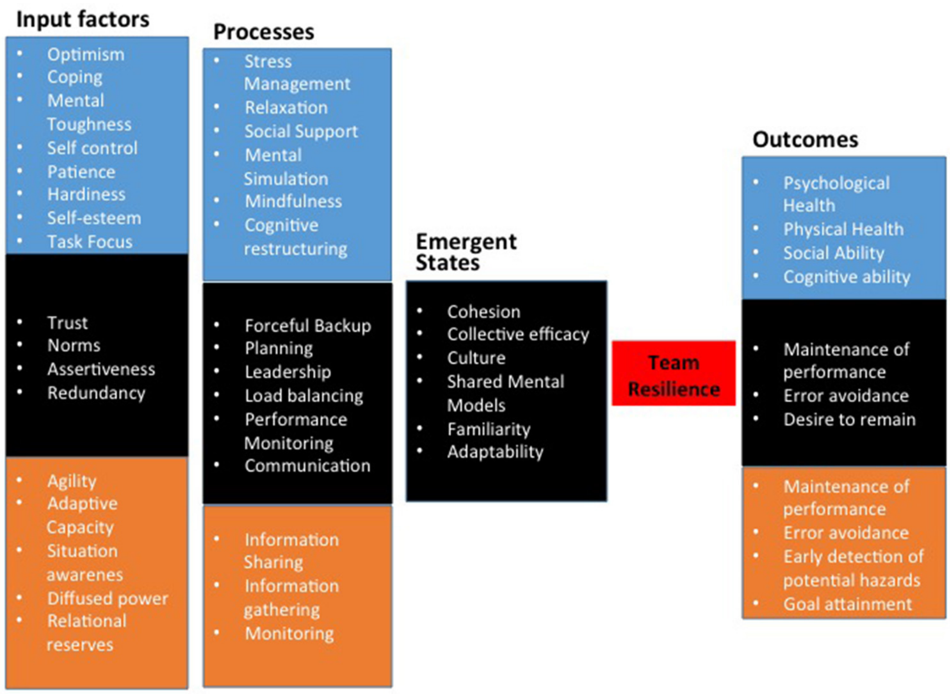

FIGURE 1 | Summary of variables affecting resiliency.

TABLE 4 | Team emergent states.

Level	Construct	Definition	Supporting authors
Team	Task adaptability	Ability of the team to shift their strategy to meet new or changing task demands.	Cannon-Bowers and Salas, 1998
Team	Cohesion	An engagement in and commitment to a group.	Schmidt et al., 2009; West et al., 2009; Weaver et al., 2011
Team	Collective efficacy	A group's shared belief in its capability to successfully complete a task or achieve a goal.	Morgan et al., 2013
Team	Culture	An established set of norms, rules, and behaviors that individuals within a team create for themselves.	Drinka, 1994; Morgan et al., 2013
Team	Shared mental models	A mental representation of a task, process, organization, or the team itself shared amongst team members.	Entin and Serfaty, 1999; Paton and Jackson, 2002
Team	Familiarity	Extent to which team members have personal knowledge of each other's strengths, weaknesses, preferences, styles, etc.	Smith-Jentsch et al., 2009
Team	Resilience	A dynamic process engaged in during the face of significant adversity, resulting in positive adaptation.	Luthar et al., 2000

factors at the individual, team, and organizational level. We believe that this conceptualization is reflective of the complex, multi-level, dynamic relationship among variables at the team level.

RESEARCH DIRECTIONS

The construct of emergent states allows researchers to propose hypotheses that better represent the dynamic, evolving nature of team processes and performance. However, given that this is a relatively new approach, empirical research to identify key emergent states is in its infancy. As this theoretical position is articulated, and as we develop new statistical tools to allow us to validate these models, we are learning more about the complex nature of team processes and the psychological states that result from team interactions.

In this paper, we have suggested a "second-order" emergent state of team resilience which might help us to understand how certain teams are able to cope with extreme stressors and to maintain their performance. More specifically, as an emergent state, this suggests that resilience may be the *result* of a number of team actions or processes, rather than a process in it of itself. Additionally, given the process vs. state debate in the literature, the nature of the construct of team resilience is certainly

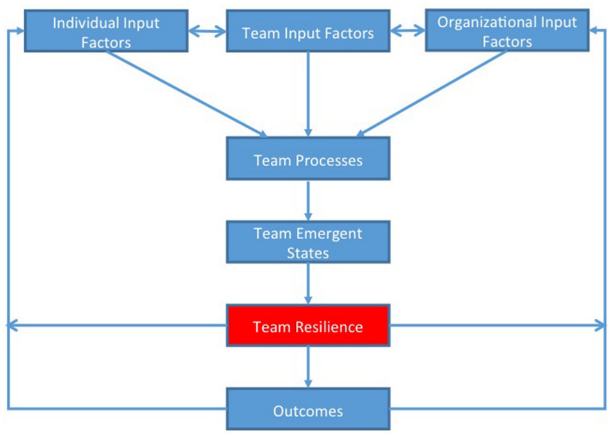

FIGURE 2 | Visual depiction of model.

unclear. Thus, a new conceptualization of team resilience is warranted. As articulated throughout the present work, viewing team resilience as an emergent state may offer insight into the nature of team resilience that prior conceptualizations have failed to achieve. Ultimately, this is a hypothesis that will need to be validated using modeling approaches. However, it is important to articulate specific relationships that will be the foundation of these models. To that end, we propose the following first-order emergent states that we hypothesize will be related to the second-order emergent state of team resilience.

1. Collective Efficacy: Collective efficacy is typically defined as the team shared belief that it possesses the capability to achieve its goal. The relationship between collective efficacy and team performance has been demonstrated several times (see Gully et al., 2002, for a review). Collective efficacy is thought to work by influencing the amount of effort that team members are willing to invest and the degree of frustration they are willing to tolerate in pursuing team goals (Gully et al., 2002). These mechanisms are likely to be particularly important during times of high stress (Jex and Gudanowski, 1992). Therefore, we hypothesize that the emergence of collective efficacy will be positively related to team resilience. This position is supported by the results of Sharma and Sharma (2016) who included collective efficacy as a latent factor in their measurement model of team resilience. Similar support was reported by Morgan et al. (2013).
2. Team Cohesion: Similar to collective efficacy, team cohesion is an attitudinal state that is related to the degree to which team members value being in the team and their commitment to remaining in the team. Although, team cohesion is thought to also exert its influence through motivation, research has indicated that it is likely a different construct than collective efficacy (Paskevich et al., 1999). Specifically, team cohesion may influence performance through elements of mutual trust and the acceptance of, and adherence to, group norms (Carron et al., 2002). Adherence to group norms is an element that is thought to be a critical element in maintaining team performance under periods of high stress (Stevens et al., 2015). Cohesion is often included in theories of team resilience (Hind et al., 1996; Meredith et al., 2011). For example, Morgan et al. (2013) describe it as an element of collective efficacy. However, we might argue that it is better included in their construct of group identity. Nevertheless, it seems reasonable to suggest that cohesion is related to the emergence of resilience.
3. Shared Mental Models: Shared mental models have been defined as a collective representation of a task, process, organization, or team (Entin and Serfaty, 1999). Shared mental models have been linked to team performance under stress because they allow team members to coordinate their activities with the cognitive load of overt communication (Rouse et al., 1992). Several empirical studies have indicated the importance of shared mental models in allowing teams to maintain their performance when confronted with stress (e.g., Bolstad and Endsley, 1999; Stout et al., 1999; Mathieu et al., 2000). Interestingly, the emergence of shared mental models is rarely considered in theories of team resilience. However, the empirical data suggest that they may be a critical first-order emergent state.
4. Team Adaptability: Team adaptability refers to the ability of the team to recognize that a given strategy is not working and to adapt their strategy to meet the new demands (Cannon-Bowers and Salas, 1998). Team adaptability encompasses a number of behaviors and abilities that involve monitoring, problem-solving, and so forth. In fact, team adaptability is frequently used interchangeably with resilience in the lay literature. While similar, there are a few notable differences. First, we argue that adaptability is an emergent state that allows team members to perform in the short-term, whereas resilience allows them to grow and develop to facilitate performance in the longer term. Secondly, adaptive expertise has been defined as the ability to invent new procedures and make novel predictions based on extant knowledge (Hatano and Inagaki, 1986). Adaptation is considered to be evidenced when the individual responds successfully to changes in the task (Smith et al., 1997). However, resilience is typically demonstrated in response to adverse (rather than simply novel) events. It is a complex process comprised of processes whereby team members use their individual and collective resources to protect the group from stressors and positively respond when faced with adversity. As such, because resilience is independent of learning activities, it represents a greater repertoire of capabilities than adaptability alone. Finally, unlike the work on adaptability by Kozlowski and colleagues (e.g., Kozlowski et al., 1999, 2009) which places critical importance on the team leader, resilience also focuses on team development without emphasizing any particular team member. Instead, resilience work tends to place equal importance across all team members. In contrast, work by Kozlowski and colleagues places emphasis on how team *leaders* must build team capabilities. In particular, they note that planning and organizing, monitoring and acting are "executive *leadership* functions." In the realm of resilience

work, these tasks are also critical but equally distributed across team members. That said, there is no question that adaptability is a critical emergent state for the development of team resilience.

AUTHOR CONTRIBUTIONS

All authors listed have made a substantial, direct and intellectual contribution to the work, and approved it for publication.

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