International Journal of Gaming and Computer-Mediated Simulations
Volume 14 • Issue 1

Using Collective Metrics to Assess Team Dynamics and Performance in eSports

Justin W. Bonny, Morgan State University, USA*
https://orcid.org/0000-0002-1601-5114

ABSTRACT

A challenge posed by virtual teams is monitoring team interactions remotely. Research with field-based soccer teams provides evidence that measures of collective behavior can be used to assess the dynamics of sports teams. Collective behaviors calculated using the spatial characteristics of teammates as they moved across the field have been found to vary by the state of the soccer match, including ball possession and proximity to a goal. The present study examined whether similar effects were observed with collective metrics calculated from players of a car-soccer eSport video game. A set of matches were retrieved and used to calculate collective behavior metrics based on the placement of teammates within a virtual arena. A subset of metrics varied by team location and ball possession, aligning with and extending previous field-based soccer research, and correlated with team performance. This suggests that collective behaviors can be used to assess aspects of team dynamics within virtual environments.

KEYWORDS

Cohesion, Coordination, Small Groups, Team Synchrony, Video Games, Virtual Teams

INTRODUCTION

Indicators of small team dynamics developed for traditional field-based sports could be used to measure eSports teams. Small teams are formed to achieve goals in a variety of formal and informal settings. Ranging from warfighter units to recreational sports, small teams are when a group of two or more individuals work together to achieve a goal (Kozlowski & Bell, 2013). Increasingly, virtual teams are forming and performing in electronic sport (eSport) environments (Pedraza-Ramirez et al., 2020). eSports span multiple video game genres and game mechanics (Pedraza-Ramirez et al., 2020), and vary in whether individual players or teams compete against each other. Despite this variability, eSports are generally defined as video games that contain an organized method for players to compete against each other during tournaments and other competitive events following a set of standardized rules (Bányai et al., 2019). For team-based eSports, measuring team effectiveness can be particularly challenging as members are frequently located at different geospatial locations and communicate

DOI: 10.4018/IJGCMS.315604

*Corresponding Author

via computer-mediated channels (Kirkman et al., 2002). With evidence that effectiveness is lower in virtual compared to physically co-located teams (Furumo & Pearson, 2006), the ability to assess the state of virtual teams could provide ways to predict and improve eSport team performance. The present research investigated a novel approach to remotely measure the interactions and dynamics eSports teams: use location-based collective behavior measures previously developed to assess physically co-located teammates. The objective of the present study was to evaluate whether the collective behaviors of eSports teams relate to team dynamics.

Measures of collective behavior have previously been developed and applied to the field-based sport soccer. Collective behaviors refer to coordinated actions of individual members of a team (López-Felip et al., 2018). With regard to soccer, research has focused on spatial placement of players across a field during a match (Duarte et al., 2013). Several competitive eSport video games based on soccer-like mechanics have been developed and widely played by the eSport community. However, collective metrics developed for field-based soccer have yet to be applied to team-based eSport games. The present study examined the extent to which measures of collective behaviors, developed for field-based soccer, can be adapted to assess team dynamics as members perform in virtual environments, specifically, a team-based video game. If similar effects are observed, this would indicate that collective metrics could be applied to team-based eSports across video game genres.

Team Effectiveness and Collective Behavior

Members of effective teams tend to display higher levels of coordination. Higher performance when working towards an objective and a greater chance to remain and perform together in the future are key features that distinguish teams with higher versus lower effectiveness (Sundstrom et al., 1990). Team coordination, the extent to which team members align their actions with each other, in particular has been identified as a key contributor to team effectiveness (Mathieu et al., 2019). Coordinating the timing, type, and location of teammate actions has been argued to be key for implementing tactics in team-based sports (Eccles, 2010). Indeed, sports research has observed that teams that display higher levels of coordination tend to be more successful at executing plays (Pina et al., 2017).

The level of coordination displayed by the collective behaviors of a team can provide insight into other attributes of the team. Eccles (2010) discussed how high levels of coordination among players requires a shared knowledge state, a common representation of the task at hand, including how to perform and align current and future actions to achieve the goal. This requires that each player has the requisite experience and skill of the sport to guide their own actions as well as perceive, interpret, and anticipate current and future actions of their teammates. In this manner, observing the collective behaviors of a sports team can provide insight into the shared knowledge of the players and can allow for predictions to be made about the effectiveness of the team.

Metrics of Collective Behavior in Field-Based Soccer

Research examining field-based sports, such as soccer, provides a potential method for inferring real-time coordination in virtual environments via collective behaviors. Specifically, previous research has used the movements and locations of soccer players across the field to create a set of collective behaviors intended to capture team dynamics. A subset of metrics that have frequently been used across studies include: team centroid (mean location of team players on the longitudinal and lateral axes of the field; Clemente et al., 2013), team stretch (sum of the distance of each player from the team centroid; Bourbousson et al., 2010), team area (the area of the polygon created by the position of each player; Clemente et al., 2013), and team synchrony (extent to which the longitudinal movements of players were coupled; Folgado et al., 2018; López-Felip et al., 2018). Past studies have evaluated the connection between calculated metrics of collective behavior and team dynamics by testing whether metrics vary by the state of a match. In these studies, collective metrics have been observed to vary when the team possesses the ball, by the position of the team on the soccer field, and covary across opposing teams (Clemente et al., 2013; Duarte et al., 2013). Additionally, collective metrics have been found to differentiate between gameplay styles, such as whether soccer teams engage in 'man-to-man' or 'zone' defense (Frias & Duarte, 2014). This has supported the use of position-based collective metrics as indicators of team dynamics in soccer.

Collective Behaviors in Team-Based eSports

It is likely that measures of collective behavior from field-based soccer can be applied to virtual environments that contain playing fields. There are substantial differences in the manual actions and knowledge required for a player to move a ball physically across a field versus by controlling an avatar within a virtual arena. However, it is predicted that if metrics of collective behavior reflect team coordination, they should apply to physical and virtual environments. Recalling the shared knowledge hypothesis of Eccles (2010), team coordination requires knowledge of the tactics and actions relevant to the current and future states of a match. Although the specific actions and tactics may vary, to be successful, the coordination of player actions suggests that they have a shared representation of the match. Such position-based collective metrics can be generated for eSports games where players need to navigate a shared virtual environment.

Recent research has highlighted eSports as a domain for examining team coordination (Lipovaya et al., 2018). Team coordination in eSports has previously been examined using qualitative interviews and ratings, with evidence that teams strive to coordinate their actions (Freeman & Wohn, 2019). Quantitative approaches have been developed to analyze the performance of teams during matches. For example, a tool has been developed to visualize the behaviors and locations of CS:GO players to review team performance (Xenopoulos et al., 2022). Player metrics have also been used to predict the probability of a team winning a match in other eSport genres. For example, statistical models developed in previous research have indicated that the team win probability was connected with the distance to the objective in a first-person shooter (Xenopoulos et al., 2020), the distance of team members across a multiplayer online battle arena (MOBA) map (Rioult et al., 2014), and resources collected during the real-time strategy game, StarCraft II (Białecki et al., 2022). The subset of associations observed with the location of team members suggests a similar connection may be observed with collective metrics and team dynamics. Additional support comes from research investigating car-soccer. Position-based measures of player behaviors have also been found to correlate with car-soccer performance. Metrics of individual players of *Rocket League* during one-versus-one matches were connected with the rank and skill of players including how much time the player spent positioned between the ball and their own goal (Smithies et al., 2021). Furthermore, teams of two to four players that together expressed positive facial expressions to a greater extent during *Rocket League* also reported greater team cohesion (Bonny, 2022). Such connections suggest that position-based collective behavior metrics developed for field-based sports could also be used to gain insights into team dynamics during eSports.

Testing the Application of Collective Metrics to eSports: Car-Soccer

In the present study, the connections between the collective behavior of small teams and team effectiveness were examined using a team-based video game, *Rocket League* (Psyonix, LLC). In this game, which is currently the most popular title in the hybrid car-soccer genre, players control virtual cars as they 'hit' a ball around an arena, attempting to score on the opponents' goal. This type of team-based video game was selected for two main reasons. First, a subset of game mechanics is shared with traditional sport soccer, such as hitting a ball into an opponent's goal, other video game genres, such as controlling a race car, and unique ones, such as using rocket boosters to propel through the air. This offered a strong test of whether collective behaviors previously developed for soccer would transfer to an eSport that had partially overlapping game mechanics. Observing collective behavior metrics effects within this genre would suggest it is likely that those developed for field-based soccer could be used to assess team interactions in eSports, more broadly. Second, although a team-based game, individual players had much freedom regarding whether to coordinate their actions with their teammates or act independently. The dimensional scaling model of small teams proposed by

Hollenbeck and colleagues differentiates teams based on the level of specialization each teammate has (skill differentiation), the length of time teams have been, and will continue to be, performing together (temporal stability), and the extent to which members of a team has equal responsibility to make team decisions (authority differentiation) (Hollenbeck et al., 2012). The structure of matches within the car-soccer game allowed for initial comparisons to be made across two of these dimensions, temporal stability and skill differentiation. About temporal stability, players could select whether to play a match with a familiar set of teammates that they previously performed with or a set of randomly assigned teammates. For competitive matches, teams composed of players with a similar ranking, based on history of performance, would play against each other. Examining teams with lower versus higher rankings offered an approximate comparison of teams with less versus more skill. Due to the novel approach of applying field-based soccer collective metrics to eSports, the goal of the present study was to investigate whether said metrics were affected by the state of the eSport match, like soccer, and related to team outcomes.

To assess the impact of game state on collective behavior metrics, differences due to the location of the team along the field and team ball possession were examined. Collective metrics that have previously been observed to vary by the game state of field-based soccer matches were selected for the present study: team centroid position, team area, team stretch index, and team position synchrony. Additionally, the correlation between the collective metrics of each team during a match was evaluated. To investigate connections with team performance, team statistics from the car-soccer match were collected including number of goals scored by the team and the number of goals saved by the team. An extension of field-based measures of collective behavior was to include the height of the player cars within the virtual arena. The cuboid virtual arena contained vertical sides and a ceiling, in addition to the field. For the car-soccer game, players could launch and guide their car vertically across the field. Although this game mechanic was distinct from field-based soccer, it offered the opportunity to examine whether measures of collective behavior, developed for a horizontal field, also extended to vertical positions within a virtual arena. It was hypothesized that collective behavior metrics would vary by the location of the team on the field, by ball possession, by teammate type, and would correlate with team performance.

METHOD

Data Collection

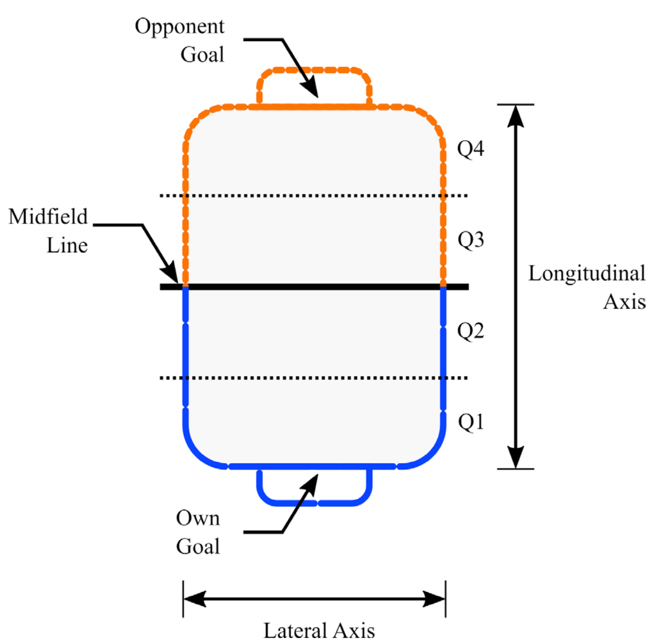
Position-based collective behavior metrics require the location coordinates of teammates during a match. Field-based sports have used various methods to track the locations of players on a field or arena and digitize the coordinates using cameras and tracking devices (Bourbousson et al., 2010; Clemente et al., 2013). Depending on the title, eSports games can provide the location of players via a match record file, an application programming interface (API), or coordinates can be inferred using computer vision. For the title of the present study, *Rocket League,* match replay files that contained records of player actions and locations were used to extract player coordinates. To play the car-soccer game, remotely-located players were connected to an online game server. While completing a match, players could visually view other players on the virtual field and had limited communication with each other. During a match, players were able to use their cars to hit the ball and cars of other players while driving around a virtual arena. Online platforms allow players to upload and share a record of the matches they completed with other players online. A sample of these uploaded matches were retrieved from publicly-available online repositories (*Ballchasing*, n.d.). Sampling criteria were that the matches were completed using the same version of the video game, the outcomes of the match would impact the ratings of the players' skill ('ranked' matches), and the team size was three players. Matches were sampled from two different match types: matches where teams were composed of players familiar with each other (standard) and of randomly selected players (solo standard). Players who uploaded the matches could also report the rank level of their team. To estimate the impact of player rank, matches were sampled from three ranking tiers (from lower to higher): silver, platinum, and champion. Teams from the retrieved matches were included for analysis if location data for all three players were present for the entire duration of the match. Prior collective behavior research with soccer has observed large effect sizes when investigating the correlation of metrics across opposing teams ($r = .62$; Duarte et al., 2013) and a small effect for ball possession (Cohen's $f = .23$; Clemente et al., 2013). A power analysis estimated a sample size of 40 would achieve statistical power of .80 for a main effect of ball possession. A total of 159 matches (52 silver, 56 platinum, 47 champion), yielding 250 teams (82 Silver, 93 Platinum, 75 Champion), were included for analysis.

Data Processing

Player location, player status, and team performance metrics, from each retrieved match were extracted using a publicly-available tool (Fausak, 2018). These parameters were automatically tracked by the video game. Prior to calculating collective behavior metrics, location data from each match was resampled using linear interpolation to 20 Hz within the MATLAB environment and stoppages of play (e.g., after a goal was scored) were estimated and removed. For each remaining time sample, the team in possession of the ball was identified and the quadrant of the field the team was located within was calculated (Figure 1). The specific size of the virtual arena could vary across matches. To account for differences in arena size, the maximum longitudinal and lateral locations of the soccer ball during a match was identified and controlled for during statistical analyses. The matches recorded the position of players using virtual units for the longitudinal (goal-to-goal, recorded as Y-axis), lateral (sideline-to-sideline, recorded as X-axis), and vertical axes (field to arena ceiling, recorded as Z-axis). At the beginning of each match, the ball was placed at the center of the field (at field level height); the center of the field served as the origin point (0,0) for the X- and Y-axes.

Collective behavior calculations for each team for each frame were based on previous research. Based on Frencken and colleagues (2011), the centroid of the team was calculated as the mean position

Figure 1.
Diagram of field dimensions and features within virtual car-soccer arena (not drawn to scale)



of all players along the X-, Y, and Z- axes, with the addition of the Z-axis being novel for *Rocket League*. Similar to López-Felip and colleagues (2018) the Y-axis centroid of the team was used to determine the quadrant of the field that the team was located. Quadrant was coded with respect to the team's own goal, increasing from the quadrant that contained their own goal (Q1) to the quadrant that contained the opponent team's goal (Q4). During analysis, contrast codes were used to account for changes in field longitudinal space available to teams, with less space available near goals (Q1, Q4; contrast code = -1) and more available in middle portion of the field (Q2, Q3; contract code = 1). This is in line with research indicating that the compressing field size can impact collective behaviors (Folgado et al., 2019). Stretch index, the distance of each player from the centroid of the team was summed into one score, with greater values indicating greater dispersion of players from the centroid, similar to Bourbousson et al., (2010). The area encompassed by the team was calculated as the size of the 2D triangle formed by the position of the three players in three-dimensional space of the arena. Following previous research (Duarte et al., 2013), the synchrony in the position of players along the longitudinal (Y) axis of the field was calculated using a cluster phase analysis MATLAB script (Richardson et al., 2012). This resulted in an estimate of synchrony, reflecting the coupling of the relative phase of player movement with respect to the phase of the group ranging from 0 to 1, with values closer to 1 indicating increasing synchronization (Richardson et al., 2012). These collective behavior metrics can be computed with digitized player coordinates from eSports titles that, like *Rocket League*, require players to navigate an environment.

To examine the impact of ball possession and field quadrant on collective behavior metrics, the mean metric was calculated for all frames that corresponded to the ball possession and quadrant for a team during a match. For some matches, collective behavior metrics could not be estimated for a team due to missing values for a player. Data used for statistical analyses are available via the online repository Open Science Framework (https://doi.org/10.17605/OSF.IO/X3JMP).

RESULTS

Two sets of statistical analyses were conducted to evaluate collective behavior metrics as indicators of team dynamics. The first set of analyses examined the extent to which collective metrics displayed effects similar to field-based soccer. First, the impact of ball possession and field quadrant on collective metrics from teams was examined using linear mixed models via the R packages 'lme4' (Bates et al., 2015) and 'lmerTest' (Kuznetsova et al., 2017) (Satterthwaite's method was used to approximate degrees of freedom). Second, correlations between collective metrics of each competing team during a match were assessed. The second set of analyses investigated connections between collective metrics, team composition, and team performance. This included a test of whether teammate type (familiar, random) and player self-rank level affected collective metrics. Next, the extent to which team goals scored and saved were related to collective metrics was evaluated. For analyses involving team centroid and field quadrant, separate models were used for the lateral (X-axis) and vertical (Z-axis) components; the longitudinal (Y-axis) component was omitted due to being used to define the quadrant a team was located within. All statistical tests were two-tailed with an alpha of .05. To control for multiple comparisons, p-values for each set of analyses were adjusted using false-discovery rate (FDR). Graphs were generated using the 'ggplot2' R package which is a library for plotting datasets (Wickham, 2016).

Influence of Ball Possession, Field Position, and Opponent Team

The impact of field quadrant and ball possession on collective behaviors was examined using a set of two-step linear mixed models (random intercept for match). For each metric, the initial step contained the baseline model, including the intercept, control variables (centroid X-axis: estimated lateral arena size; area and stretch index: estimated longitudinal and lateral arena size, team rho: longitudinal arena size). For the second step model, the main effects of, and interaction between, ball possession (levels:

own, opponent) and field quadrant (levels: Q1, Q2, Q3, Q4; contrast coded -1, 1, 1, -1) were added. When comparing the two-step models, improvements in fit by adding the factors were observed for centroid Z-axis, χ^2 (3) = 523.93, adj. $p < .001$, area, χ^2 (3) = 1791.93, adj. $p < .001$, stretch index, χ^2 (3) = 2414.77, adj. $p < .001$, group rho, χ^2 (3) = 2149.26, adj. $p < .001$, but not centroid X-axis, χ^2 (7) = 2.05, adj. $p = .563$.

The remaining significant second-step models provided evidence that collective behavior metrics varied by match state (Table 1). Main effects were observed for field quadrant for each measure and for ball possession for centroid Z-axis, area, and stretch index. A significant interaction was observed for area and stretch index (Table 1). Both area and stretch index metrics displayed similar effects: greater metric values were observed within the inner quadrants (Q2, Q3) compared to the outer quadrants (Q1, Q2) and when the opponent had possession of the ball. For both measures, the significant interaction was characterized by a greater effect of ball possession for inner compared to outer field quadrants (Figure 2). For centroid Z-axis, greater values were observed when the team had possession of the ball and in the outer (Q1, Q4) compared to inner (Q2, Q3) quadrants. Similar to centroid Z-axis, group rho was greater in outer compared to inner field quadrants. These findings provided evidence that centroid, stretch, and area metrics varied by the position of the team on the field and possession of the ball.

The next set of analyses examined the extent to which collective behavior metrics for opposing teams were correlated during a match. To estimate the correlation, for each match and collective behavior, the Pearson *r* correlation coefficient was calculated using metric values for each team for all in-play frames during a match. One-sample t-tests were used to assess whether the correlation coefficients across matches were significantly different than zero. Significant effects were observed for centroid X-axis position, mean $r = .675$, $t(154) = 83.09$, $p < .001$, centroid Y-axis position, mean $r = .775$, $t(154) = 134.91$, $p < .001$, centroid Z-axis position, mean $r = .225$, $t(154) = 20.54$, $p < .001$, and group rho, mean $r = .203$, $t(105) = 14.35$, $p < .001$. No significant effects were observed for area, mean $r = .005$, $t(132) = 62$, $p = .539$, or stretch index, mean $r = -.014$, $t(144) = -1.43$, $p = .156$. This indicates that the positioning of the team on the field was associated with the position of the opposing team.

Impact of Team Rank, Match Type, and Team Performance

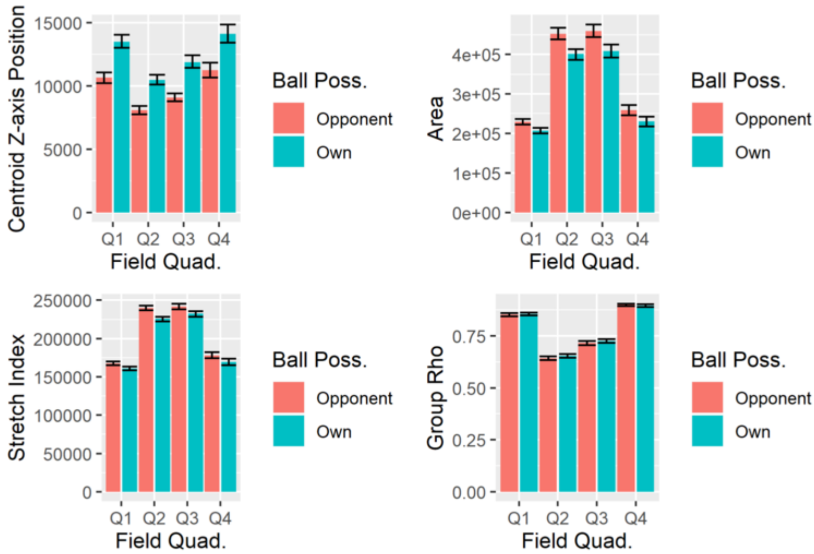
The next set of analyses examined whether mean collective metrics for teams during a match were connected with characteristics of the team players as well as team performance. For this set of analyses, the centroid Y-axis was adjusted so that for both opposing teams, Y-axis positions near their respective goals were positive and positions near the opposing team were negative.

To examine differences due to team composition, collective metrics for a match were compared across teams that had familiar versus randomly assigned teammates and the skill rank players self-identified as. For self-reported ranks, contrast codes were used to reflect the differences in rank across matches, with higher values indicating higher ranks (1 = Silver, 2 = Platinum, 3 = Champion). Linear regressions, with factors of match type and self-rank (and corresponding estimated arena size

Table 1.
Effects of field quadrant (field quad.) and ball possession (ball poss.) on collective behaviors

Effect	Centroid Z-axis	Area	Stretch Index	Group Rho
Field Quad.	$F(1.00, 2145.30) = 269.58$, $p < .001$, Cohen's $f = .35$	$F(1.00, 2141.76) = 2692.09$, $p < .001$, Cohen's $f = 1.12$	$F(1.00, 2140.12) = 4376.92$, $p < .001$, Cohen's $f = 1.43$	$F(1.00, 1890.66) = 3990.70$, $p < .001$, Cohen's $f = 1.45$
Ball Poss.	$F(1.00, 2145.31) = 323.17$, $p < .001$, Cohen's $f = .39$	$F(1.00, 2141.76) = 100.21$, $p < .001$, Cohen's $f = .22$	$F(1.00, 2140.12) = 95.46$, $p < .001$, Cohen's $f = .21$	$F(1.00, 1890.66) = 3.73$, $p = .054$, Cohen's f = .04
Field Quad. x Ball Poss.	$F(1.00, 2145.31) = .70$, $p = .404$, Cohen's $f = .02$	$F(1.00, 2141.76) = 11.51$, $p = .001$, Cohen's $f = .07$	$F(1.00, 2140.12) = 5.12$, $p = .024$, Cohen's $f = .05$	$F(1.00, 1890.66) = 3.73$, $p = .054$, Cohen's $f = .04$

Figure 2.
Collective behavior metrics by field quadrant of team and ball possession. Error bars indicate 95% confidence intervals



dimensions), accounted for a significant amount of variance for centroid Z-axis, $F(2, 247) = 175.41$, adj. $p < .001$, $R^2 = .587$, area, $F(4, 245) = 26.22$, adj. $p < .001$, $R^2 = .300$, and stretch index, $F(4, 245) = 14.67$, adj. $p < .001$, $R^2 = .193$, but not for centroid X-axis, $F(3, 246) = .95$, adj. $p = 1$, $R^2 = .011$, centroid Y-axis, $F(3, 246) = 2.71$, adj. $p = .276$, $R^2 = .032$, or group rho, $F(3, 246) = 1.49$, adj. $p = 1$, $R^2 = .018$. For centroid Z-axis, area, and stretch index, significant effects for teammate type and self-rank (*ps* < .01) with a similar pattern were observed: metric values were higher for randomly assigned versus familiar teammates and values increased with self-rank. Overall, higher-ranking players and teams assembled by match making algorithms were more spread apart on the field and higher in the air when they played matches.

Connections between collective behavior metrics and team performance statistics for matches were next examined. To account for the count-based performance variables, goals scores and goals saved, Spearman rho coefficients were calculated. A significant negative correlation with goals scored was observed with centroid Y-axis position, indicating that teams closer to the opponent goal (negative position values) tended to score more goals (Table 2). Significant positive correlations with goals saved were observed with centroid Y-axis positions closer to the team's goal, teams that encompassed greater area, centroid Z-axis positions higher above the field, and teams with players dispersed further from the centroid (stretch index). A significant negative correlation with saves was observed with group rho indicating teams with greater synchrony in movement across the longitudinal axis tended to have fewer saved goals. Next, to examine the relative impact on match outcome, a logistic regression predicting whether the team won the match (132 won, 112 lost) using collective metrics (field dimensions included as control variables) was calculated using Mplus (MLR estimator). Of the metrics, Y-axis centroid was a significant predictor of winning a match, with teams that remained closer to their goal (indicated by greater values) being less likely to win a match, odds-ratio = .92 ($SE = .03$), $p = .017$ (95% confidence interval: .86, .99; all other metric *ps* > .05). Overall, teams that scored more goals and won matches were closer to the opponent's goal during matches and those that had more saves were spread apart and moved more independently closer to their own goal.

Table 2.
Descriptive statistics and correlations (Spearman's rho) between match collective behavior metrics and performance of teams

Variable	Mean	SD	1	2	3	4	5	6	7
1-Goals	2.48	1.70	---	---	---	---	---	---	---
2-Saves	2.42	1.80	-.172**	---	---	---	---	---	---
3-Centroid X-axis	3611.68	27993.61	-.010	-.075	---	---	---	---	---
4-Centroid Y-axis	93962.89	52823.44	-.251***	.290***	.006	---	---	---	---
5-Centroid Z-axis	10718.65	2592.8	-.036	.214***	.091	-.180**	---	---	---
6-Area	350624.2	87905.43	.110	.219***	-.046	-.242***	.538***	---	---
7-Stretch	208191.6	22785.78	.110	.202**	-.065	-.216***	.471***	.930***	---
8-Group Rho	.74	.05	-.089	-.192**	.108	-.144*	-.133*	-.510***	-.619***

* $p < .05$; ** $p < .01$, *** $p < .001$ *Note*: spatial metric values are in virtual units.

DISCUSSION

The present study examined collective behaviors within an eSport car-soccer video game using metrics developed for field-based team sports. The metrics were based on the virtual position of player-controlled cars as teams attempted to score goals on the opponent team while keeping the ball out of their own goal. Despite the virtual environment and multiple gameplay differences, a subset of collective behaviors displayed effects similar to what has been observed in past studies with field-based soccer. Several metrics of collective behaviors were sensitive to the arena location and ball possession of the team and correlated with team performance. Metrics also varied based on how teammates were selected and the skill of the players. These findings extend previous studies with field-based soccer to an eSport environment, including evidence that collective behavior in the vertical plane displayed similar effects to those based on the horizontal (field-level) plane. These initial findings indicate that team dynamics metrics developed for field-based soccer can be applied to the eSport environment. This supports the use of position-based collective behavior metrics as indicators of team dynamics in eSports that share at least some game mechanics with traditional sports.

Sensitivity of Collective Behavior Metrics to Game State

Like past studies with field-based soccer, collective behavior metrics in a car-soccer game were observed to vary by the state of the match. Specifically, collective behavior metrics were aggregated based on the quadrant of the field the team was located and when the team did and did not have possession of the ball. Past studies examining the impact of match state have found effects of field position, but not ball possession, on team synchrony (Duarte et al., 2013) and both types of effects for team surface area (Duarte et al., 2012). In the present study, apart from centroid X-axis position (Y-axis was omitted since it was used to define field quadrant), all collective behavior metrics varied by field position. Additionally, centroid Z-axis position, area, and stretch index varied with ball possession. The significant effect of field quadrant, but not ball possession, on team synchrony was similar to what has been observed in field-based soccer matches (Duarte et al., 2013). Parallels to field-based soccer were observed with correlations between the metrics of opposing eSport teams during matches. Similar to field-based soccer players (Clemente et al., 2013), positive correlations were observed with the centroid axis positions of eSport teams in the present study, and this was extended to the vertical centroid axis as well. Additionally, like past field-based soccer teams (Duarte et al., 2013), a significant correlation was observed in the group synchrony of opposing eSport teams. These results suggest that within a virtual arena, the position-based collective behavior metrics were influenced by match state and displayed similar effects to those previously observed in field-based soccer. This is particularly notable since the gameplay of the eSport game included mechanics not observed in field-based soccer, such as using rockets to move the car through the air, and the additional vertical spatial dimension

Collective Behavior Metrics related to Team Composition and Performance

The method of teammate selection and player rank influenced a subset of team collective behaviors. Specifically, centroid Z-axis, area, and stretch index were greater during a match for teams composed of randomly selected players and with higher ranks. That metrics increased with rank suggests that players that self-reported being at a higher skill level may have engaged in different types of behaviors during a match compared to lower-skill players. Similarly, the types of behaviors engaged by players may differ when teams were created with players familiar with each other versus randomly assigned. How actions taken by players vary by skill level and selection process, contributing to differences in collective behavior metrics, remains to be determined. Furthermore, the increase in metrics with teammate selection and player rank indicates that different aspects of team composition could have similar changes in collective behaviors. This highlights that collective behaviors were likely influenced by multiple team factors. Identifying these factors should be the subject of future research.

In the present study, two performance metrics were significantly correlated with collective behaviors, goals scored and goals saved. The connection with goals scored was observed with the position of the team centroid on the longitudinal (Y) axis. This indicated that teams that were on average closer to the opponent goal across a match, scored more goals. The reverse was observed with goals saved, teams that were closer to their own goal during a match recorded more saves. In addition to longitudinal axis, teams that had a higher vertical position during the match recorded more saves. This may be due to actions associated with saving a goal; players could launch their car vertically to block a goal. More saves were also associated with greater mean surface area and dispersion (stretch index), but lower synchrony (group rho). This may reflect tactics used by teams. Although the type of role a player assumed at the beginning of a match was not fixed (i.e., there were no fixed "goalie" or "striker" positions assigned to players), players could decide what roles to assume during a game. A strategy to save the ball from entering the goal was to have one member remain by the goal, while the other members attempted to score a goal. This level of coordination would lead to a reduction in movement synchrony between the goalie and their teammates and greater amount of space covered by the team. When predicting whether a team won a match, the longitudinal position of a team remained a significant predictor when combined with other collective metrics. This suggested that teams that, on average, were located farther from their own goal and closer towards the opponent goal were more likely to win the match. This aligns with evidence that the positioning of Rocket League players during a match is associated with their self-reported rank, an indicator of skill (Smithies et al., 2021). Combined with past research with soccer team performance, these results suggest that that the collective behaviors in the present study reflected tactical behaviors of eSport teams that influenced match performance.

Future Directions and Applications

The present study provides an initial demonstration that specific types of collective metrics during eSport matches, based on the virtual locations of players, are sensitive to team dynamics. This novel finding suggests that eSports that share game mechanics with real-world sports could also use collective behavior metrics to analyze team performance. The causal forces behind relations between collective behavior metrics, team composition, and team performance remain to be determined. In line with research examining such metrics in field-based sports (Bourbousson et al., 2010; Duarte et al., 2013), collective behaviors may reflect team coordination to execute tactics during matches. In line with this is the view that coordinating behaviors between teammates requires a shared knowledge representation, indicative of team dynamics (Eccles, 2010). That correlations were observed between a subset of metrics and team performance aligns with collective behaviors being indicators of team dynamics. Alternatively, the collective behaviors displayed in the present study may have been due to coincidental alignment of player actions, rather than planned tactics. For example, increases in the vertical position of the team centroid may not have been due to an explicit tactic of a team but rather all players launching their cars vertically to get to the ball traveling through the air. Future studies that explicitly manipulate team tactics relevant to eSports, similar to previous research that had field-based soccer players engaged in 'man-to-man' or 'zone' defense (Frias & Duarte, 2014), will be better positioned to examine the relation between collective behaviors and explicit coordination in team-based video games.

Taking a temporal-based approach when calculating collective metrics during a match could provide further insight into how team dynamics relate to match events and team actions. Like previous field-based soccer research, the present study focused on mean collective metrics across portions of car-soccer matches. Although suitable for an initial investigation, taking a temporal approach, with analyses focused on time-series data, could provide greater insight into what types of team coordination actions aligned with collective metrics. Similar approaches have been used with location-based metrics when predicting team performance in other eSport genres (Rioult et al., 2014; Xenopoulos et al., 2020). Incorporating information from other modalities used by teams during matches with the collective metrics of the present study could provide further insight into team dynamics. For example, toxic behaviors in MOBA eSport matches have been found to occur on teams via either text-based communication between players or types of player actions (e.g., sabotaging team; Kou, 2020). Using such information in conjunction with collective metrics could enable greater accuracy in modeling team dynamics within eSport teams. An additional application of temporal-based metrics is for post-hoc review and training of eSport teams. Similar to tools developed for field-based sports, such as baseball (Dietrich et al., 2015), having near-real time collective metrics could enhance insight into how an eSport team is performing during training exercises as well as when reviewing the dynamics of teams after completing a match.

Future research should examine the application of collective behaviors to other team-based eSports. The use of player position is applicable to a number of eSport genres that also have players control avatars within a virtual space, such as multiplayer online battle arenas (MOBAs) and first-person shooters (FPS). Additional measures of collective behaviors, based on game-specific actions, could also be developed to examine collective actions beyond movement. The many video game genres that use teams of players as the main game mechanic offer an opportunity to examine multiple types of collective actions and how they relate to team dynamics. Collective behaviors of teams can be included as additional types of input in algorithms predicting the outcomes of eSports matches (Hodge et al., 2021; Ke et al., 2022; Xenopoulos et al., 2020). As sports betting in eSports has increased, so to has interest in using in-game analytics to predict match outcomes (Lopez-Gonzalez & Griffiths, 2018; Sweeney et al., 2021). Applying collective behavior metrics that reflect team dynamics could provide additional predictive power in assessing which teams are more likely to prevail.

REFERENCES

ballchasing. Retrieved October 9, 2019, from ballchasing.com

Bányai, F., Griffiths, M. D., Király, O., & Demetrovics, Z. (2019). The psychology of esports: A systematic literature review. *Journal of Gambling Studies*, *35*, 351–365. https://doi.org/10.1007/s10899-018-9763-1

Bates, D. M., Mächler, M., Bolker, B. M., & Walker, S. C. (2015). Fitting linear mixed-effects models using lme4. *Journal of Statistical Software*, *67*(1), 1–48. https://doi.org/10.18637/jss.v067.i01

Białecki, A., Gajewski, J., Białecki, P., Phatak, A., & Memmert, D. (2022). Determinants of victory in Esports - StarCraft II. *Multimedia Tools and Applications*. 10.1007/s11042-022-13373-2

Bonny, J. W. (2022). Self-report and facial expression indicators of team cohesion development. *Behavior Research Methods*. 10.3758/s13428-022-01799-3

Bourbousson, J., Sève, C., & McGarry, T. (2010). Space-time coordination dynamics in basketball: Part 2. the interaction between the two teams. *Journal of Sports Sciences*, *28*(3), 349–358. https://doi.org/10.1080/02640410903503640

Clemente, F. M., Couceiro, M. S., Martins, F. M. L., & Mendes, R. (2013). An online tactical metrics applied to football game. *Research Journal of Applied Sciences, Engineering and Technology*, *5*(5), 1700–1719. https://doi.org/10.19026/rjaset.5.4926

Dietrich, C., Koop, D., Vo, H. T., & Silva, C. T. (2015). Baseball4D: A tool for baseball game reconstruction & visualization. *2014 IEEE Conference on Visual Analytics Science and Technology, VAST 2014 - Proceedings*. 10.1109/VAST.2014.7042478

Duarte, R., Araújo, D., Correia, V., Davids, K., Marques, P., & Richardson, M. J. (2013). Competing together: Assessing the dynamics of team-team and player-team synchrony in professional association football. *Human Movement Science*, *32*, 555–566. https://doi.org/10.1016/j.humov.2013.01.011

Duarte, R., Araújo, D., Freire, L., Folgado, H., Fernandes, O., & Davids, K. (2012). Intra- and inter-group coordination patterns reveal collective behaviors of football players near the scoring zone. *Human Movement Science*, *31*, 1639–1651. https://doi.org/10.1016/j.humov.2012.03.001

Eccles, D. (2010). The coordination of labour in sports teams. *International Review of Sport and Exercise Psychology*, *3*(2), 154–170. https://doi.org/10.1080/1750984X.2010.519400

Fausak, T. (2018). *Rattletrap*. github.com/tfausak/rattletrap/

Folgado, H., Bravo, J., Pereira, P., & Sampaio, J. (2019). Towards the use of multidimensional performance indicators in football small-sided games: the effects of pitch orientation. *Journal of Sports Sciences*. 10.1080/02640414.2018.1543834

Folgado, H., Duarte, R., Marques, P., Gonçalves, B., & Sampaio, J. (2018). Exploring how movement synchronization is related to match outcome in elite professional football. *Science and Medicine in Football, 2*(2), 101–107. 10.1080/24733938.2018.1431399

Freeman, G., & Wohn, D. Y. (2019). Understanding eSports team formation and coordination. *Computer Supported Cooperative Work*, *28*, 95–126. https://doi.org/10.1007/s10606-017-9299-4

Frencken, W., Lemmink, K., Delleman, N., & Visscher, C. (2011). Oscillations of centroid position and surface area of soccer teams in small-sided games. *European Journal of Sport Science*, *11*(4), 215–223. https://doi.org/10.1080/17461391.2010.499967

Frias, T., & Duarte, R. (2014). Man-to-man or zone defense? Measuring team dispersion behaviors in small-sided soccer games. *Trends in Sport Sciences*, *3*(21), 135–144.

Furumo, K., & Pearson, J. M. (2006). An empirical investigation of how trust, cohesion, and performance vary in virtual and face-to-face teams. *Proceedings of the Annual Hawaii International Conference on System Sciences*. 10.1109/HICSS.2006.51

Hodge, V. J., Devlin, S., Sephton, N., Block, F., Cowling, P. I., & Drachen, A. (2021). Win prediction in multiplayer esports: Live professional match prediction. *IEEE Transactions on Games, 13*(4), 368–379. 10.1109/TG.2019.2948469

Hollenbeck, J. R., Beersma, B., & Schouten, M. E. (2012). Beyond team types and taxonomies: A dimensional scaling conceptualization for team description. *Academy of Management Review*, *37*(1), 82–106. https://doi.org/10.5465/amr.2010.0181

Ke, C. H., Deng, H., Xu, C., Li, J., Gu, X., Yadamsuren, B., Klabjan, D., Sifa, R., Drachen, A., & Demediuk, S. (2022). DOTA 2 match prediction through deep learning team fight models. *2022 IEEE Conference on Games (CoG)*, 96–103. 10.1109/CoG51982.2022.9893647

Kirkman, B., Rosen, B., & Gibson, C. B. (2002). Five challenges to virtual success: Lessons from Sabre. *The Academy of*, *16*(3), 67–79.

Kou, Y. (2020). Toxic behaviors in team-based competitive gaming: The case of League of Legends. *Proceedings of the Annual Symposium on Computer-Human Interaction in Play (CHI PLAY'20)*. 10.1145/3410404.3414243

Kozlowski, S. W. J., & Bell, B. (2013). Work groups and teams in organizations: Review update. In N. Schmitt & S. Highhouse (Eds.), Handbook of Psychology (2nd ed., pp. 412–469). Wiley.

Kuznetsova, A., Brockhoff, P. B., & Christensen, R. H. B. (2017). lmerTest package: Tests in linear mixed effects models. *Journal of Statistical Software*, *82*(13), 1–19. https://doi.org/10.18637/jss.v082.i13

Lipovaya, V., Lima, Y., Grillo, P., Barbosa, C. E., De Souza, J. M., & De Castro Moura Duarte, F. J. (2018). Coordination, communication, and competition in eSports: A comparative analysis of teams in two action games. *ECSCW 2018 - Proceedings of the 16th European Conference on Computer Supported Cooperative Work*. 10.18420/ecscw2018_11

López-Felip, M. A., Davis, T. J., Frank, T. D., & Dixon, J. A. (2018). A cluster phase analysis for collective behavior in team sports. *Human Movement Science*, *59*, 96–111. https://doi.org/10.1016/j.humov.2018.03.013

Lopez-Gonzalez, H., & Griffiths, M. D. (2018). Understanding the convergence of markets in online sports betting. *International Review for the Sociology of Sport*, *53*(7), 807–823. https://doi.org/10.1177/1012690216680602

Mathieu, J. E., Gallagher, P. T., Domingo, M. A., & Klock, E. A. (2019). Embracing complexity: Reviewing the past decade of team effectiveness research. *Annual Review of Organizational Psychology and Organizational Behavior*, *6*, 17–46. https://doi.org/10.1146/annurev-orgpsych-012218-015106

Pedraza-Ramirez, I., Musculus, L., Raab, M., & Laborde, S. (2020). Setting the scientific stage for esports psychology: A systematic review. *International Review of Sport and Exercise Psychology*, *13*(1), 319–352. https://doi.org/10.1080/1750984X.2020.1723122

Pina, T. J., Paulo, A., & Araújo, D. (2017). Network characteristics of successful performance in association football. A study on the UEFA champions league. *Frontiers in Psychology*. 10.3389/fpsyg.2017.01173

Richardson, M. J., Garcia, R. L., Frank, T. D., Gergor, M., & Marsh, K. L. (2012). Measuring group synchrony: A cluster-phase method for analyzing multivariate movement time-series. *Frontiers in Physiology*. 10.3389/fphys.2012.00405

Rioult, F., Métivier, J.-P., Helleu, B., Scelles, N., & Durand, C. (2014). Mining tracks of competitive video games. *AASRI Procedia, 8*, 82–87. 10.1016/j.aasri.2014.08.014

Smithies, T. D., Campbell, M. J., Ramsbottom, N., & Toth, A. J. (2021). A Random forest approach to identify metrics that best predict match outcome and player ranking in the esport Rocket League. *Scientific Reports*, *11*(1). https://doi.org/10.1038/s41598-021-98879-9

Sundstrom, E., De Meuse, K. P., & Futrell, D. (1990). Work teams: Applications and effectiveness. *The American Psychologist*, *25*(2), 120–133. https://doi.org/10.1037/0003-066X.45.2.120

Sweeney, K., Tuttle, M. H., & Berg, M. D. (2021). Esports gambling: Market structure and biases. *Games and Culture*, *16*(1), 65–91. https://doi.org/10.1177/1555412019872389

Wickham, H. (2016). ggplot2: Elegant Graphics for Data Analysis. Springer-Verlag.

Xenopoulos, P., Doraiswamy, H., & Silva, C. (2020). Valuing player actions in Counter-Strike: Global Offensive. *IEEE International Conference on Big Data*. https://arxiv.org/abs/2011.01324

Xenopoulos, P., Rulff, J., & Silva, C. (2022). GgViz: Accelerating large-scale esports game analysis. *Proc. ACM Hum.-Comput. Interact., 6*(CHI PLAY). 10.1145/3549501