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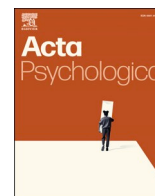
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## Task complexity and social identity interact to shape interpersonal coordination in rugby union<sup>☆</sup>

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### ABSTRACT

Grounded in an ecological dynamics framework and drawing on social identity theory, this experimental study examined how task complexity (manipulated by the defenders' initial positions) and attackers' motivational goals (either self- or team-oriented goals) interact to shape interpersonal coordination in a rugby union small-sided game. It was hypothesized that the goal priming influence player and team behaviors in high complexity situations, characterized by broader landscapes of affordances. Interpersonal coordination was analyzed at both the team and player levels through a passing network analysis integrating both the spatial dimension and the topological roles of the different players. Results showed that the manipulation of task complexity had a clear effect on team coordination patterns and on players' role within it, indicating that the attackers have adapted their passing interactions to the spatial configuration of defenders. Motivational goals' priming alone had limited effects but did interact with task complexity, particularly at the level of player roles. Overall, the findings offer some insights into how ecological dynamics and social identity processes may jointly shape interpersonal coordination in team sports, while providing methodological advances for analyzing collective behavior through network analysis.

### 1. Introduction

Team sports like rugby union can be conceptualized as complex dynamical systems, where collective behavior emerges from the actions and interactions between its components (players) in a dynamically changing environment (Passos et al., 2008). In turn, a player's behavior emerges at the performer–environment level as a result of the perception of opportunities for action, or *affordances* (Araújo et al., 2017), shaped by interacting *constraints*, including individual, task, and environmental constraints (Newell, 1986). From an ecological dynamics perspective, skilled performance relies on players' ability to attune to these affordances and adapt to the specific set of constraints (Button et al., 2021). Such adaptability is supported by the degeneracy property of

neurobiological systems, which allows complex adaptive systems (e.g., a player, a team) to develop a wide range of solutions to achieve the same outcome (Seifert et al., 2016; Whitacre & Bender, 2010). Importantly, this property is not limited to individual scale but can apply at the interpersonal scale (Edelman & Gally, 2001). This implies that similar team performance outcomes can emerge from multiple patterns of players' interactions. Accordingly, the present study models team coordination patterns and player roles within it, to investigate how players interact to succeed in a rugby union task under experimental constraints.

In team sports, *others* (i.e., teammates, opponents) participate in shaping the dynamic landscape of affordances, through their relative motion and positioning (Passos et al., 2020). Thus, some of the affordances an individual perceives are related to others: they are in that

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sense, social. *Social affordances* include: affordances for others (*i.e.*, perceiving actions that another can do), affordances of others (*i.e.*, actions that another allows the perceiver to do), and affordances for joint actions (*i.e.*, actions that a perceiver and another can perform when cooperating) (Fajen et al., 2008). It constitutes a communication channel explaining on-field interactions in team sports, whether collaborative (*i.e.*, intra-team) or competitive (*i.e.*, inter-team). For example, in rugby union, the ball carrier must be attuned to the possibilities for action offered by teammates and opponents in order to move forward and get closer to the try line. In that perspective, interpersonal coordination in team sports may emerge either from individual actions adjusted based on affordances for or of others, or from players' ability to perceive affordances for the team (Fajen et al., 2008). The former perspective has been formulated as the *shared affordances* hypothesis, which posits that team coordination emerges from reciprocal perception–action couplings among teammates (Silva et al., 2013). The latter is captured in the recent formulation of the *collective affordances* hypothesis, which accounts for players' ability to directly perceive affordances relevant for the team as a whole (Weichold & Thonhauser, 2020). This perspective draws on psychological mechanisms described in the Social Identity Theory (Haslam, 2004) which states that social groups (*e.g.*, sport teams) are not just an external feature of an individual's psychology, but rather shape it and participate in defining a person's sense of self. Put simply, individuals do not define themselves only as an “I”, but also as part of a “we”. Thus, once players' embodied social identity is activated, they would become sensitive to embodied social identity affordances – or collective affordances – which they were not sensitive to before (Weichold & Thonhauser, 2020). Accordingly, more than being attuned and adapt to individuals' action possibilities (*i.e.*, for themselves, their teammates, their opponents), players must also be attuned and adapt to action possibilities that are relevant for their team. For example, in rugby union, perceiving the opportunity to stretch the opposing defensive line by running in a given direction with the aim of creating space for the team may support effective interpersonal coordination.

Previous work in rugby union showed that the manipulation of task constraints, such as the positioning of defenders to create gaps in the defensive line, can invite the ball carrier to perform specific actions (*i.e.*, running, short passes, long passes) (Correia et al., 2012). By influencing their landscape of affordances, such task constraints can therefore shape players actions – and consequently, team coordination patterns. Likewise, the idea of collective affordances also implies that the activation of social identity can be seen as a psycho-social constraint that participates in shaping players' perception–action couplings. Namely, by fostering social identity, one could affect players' attunement to collective affordances, and thus lead to more team-oriented decisions and less self-oriented ones (Weichold & Thonhauser, 2020). Recent experimental evidence supports this hypothesis, as Guyomarch et al. (2025) revealed that basketball players decided to do more passes and less shots when their social identity was activated. Their work built on an innovative experimental methodology introduced in Campo, Champely, et al. (2019) that allows to foster players' social identity in ecological conditions through the introduction of self- versus team-oriented motivational goals. From an ecological dynamics standpoint, such procedure can be conceptualized as an individual-level constraint, as it modifies key characteristics of the organism. Specifically, it is expected to shape players' intentions, which are considered as the most important individual constraint structuring the search and selection of affordances (Renshaw & Chow, 2019). In addition, evidence that such goal manipulations influence players' emotional states (Campo, Mackie, & Sanchez, 2019) further supports the idea that social identity activation operates by constraining organismic states.

Although previous research has shown that both defenders' positioning and social identity processes can act as constraints shaping players' perception–action couplings, their potential interaction remains largely unexplored. In particular, players' social identity may be more or

less influential given other task, environmental or organismic constraints. The work of Hacques et al. (2025) provided initial evidence supporting this possibility: the question of its interaction with task complexity was investigated by studying rugby players' decision-making. The results showed that the ball-carrier appeared more responsive to available spaces for their teammates (*i.e.*, resulting in more passing actions) when their social identity was activated, and more responsive to available spaces for themselves (*i.e.*, resulting in more running actions) when it was less activated (Hacques et al., 2025). Importantly, these effects were more pronounced in a complex task, that is, a situation offering greater complexity in terms of decision-making. Thus, social identity processes appear to influence perception–action couplings primarily in tasks that afford a wider range of possible actions, while simpler tasks would constrain behavior toward more similar solutions regardless of how strongly players identify themselves as members of the team.

### 1.1. Aims of the study

Aligned with Hacques et al. (2025), the aim of this work was to investigate, at the interpersonal scale, how defenders' initial positions (*i.e.*, task constraint) and attackers' motivational goals (*i.e.*, individual constraint) interact in a small-sided rugby union game. Thus, beyond individual decision-making, the present study focuses on how these constraints influence players' interactions, studying them both at the collective and individual levels. The research question was therefore: *Does the interaction of task and individual constraints shape the emergence of team coordination patterns and player roles within it?* To the best of our knowledge, this work constitutes the first empirical investigation of the interaction between such psycho-social constraints and a spatial task constraint on interpersonal coordination in team sports.

On the one hand, motivational goals were either self- versus team-oriented, thought to activate players' social identity more or less by influencing players' level of self-abstraction – that is, their perception of “I” or “us” (Campo, Champely, et al., 2019). On the other hand, two different defense scenarios were designed to provide different levels of complexity in terms of decision-making by offering different gaps among defenders (Hacques et al., 2025). Specifically, a *low complexity* situation offered a relatively clear and obvious solution, while a *high complexity* situation offered multiple action possibilities – thus, less obvious decisions.

If these two constraints are expected to affect players' perception–action couplings, the main hypothesis was that motivational goals would primarily influence interpersonal coordination in the more complex situation. The low complexity situation will narrow down the landscape of affordances to a specific one, thereby limiting the possible influence of social identity processes. In contrast, the high complexity situation will offer a wider landscape of affordances that allows motivational goals to shape how players and teams adapt their behaviors. Specifically, it is hypothesized to affect the extent to which they rely on various coordination patterns to achieve the task: team-oriented goals would enhance players' attunement to collective affordances and lead players and teams to converge toward more consistent coordination patterns; whereas the presence of self-oriented goals could interfere more with team expectations and result in greater diversity in coordination patterns and player roles.

## 2. Method

The present study is based on data collected within an experimental protocol that has previously led to a published article (Hacques et al., 2025). This protocol was originally designed to study the effects of defenders' initial positions and attackers' motivational goals on decision-making, interpersonal coordination, and performance in a small-sided rugby union game. While Hacques et al. (2025) investigated individuals' decision-making and team performance outcomes, the present

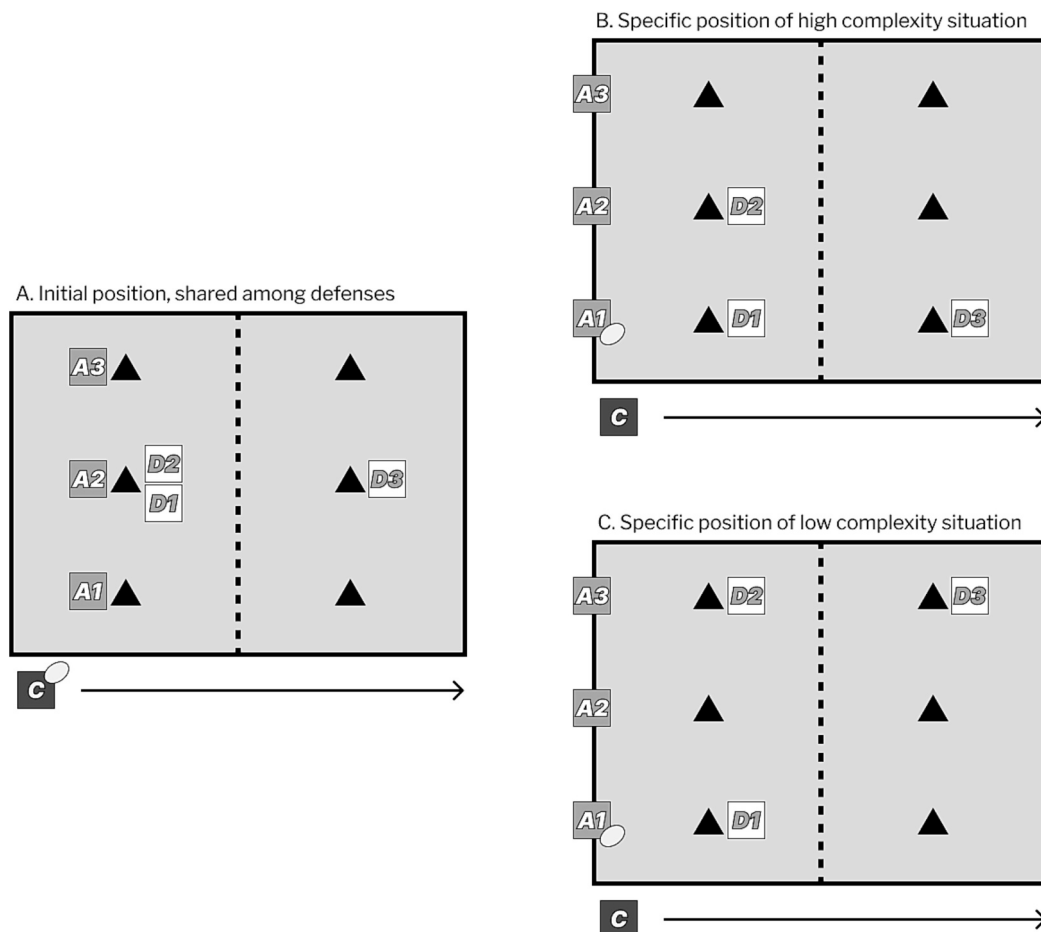
paper shifts the analytical focus to the interpersonal scale. Accordingly, different analytical methods and metrics are employed to analyze the same dataset. Participants were informed about both levels of analysis and all research questions. Also, all variables required for the present study were included in the original data collection, meaning that no additional data were collected for the present study. Thus, this data reuse complies with ethical research standards and open science principles. As the protocol has been previously described in detail in [Hacquies et al. \(2025\)](#), only a brief overview of the task and experimental settings is provided in the present work. All interested readers are referred to the aforementioned study for further details.

### 2.1. Dataset

The dataset comprised 102 elite youth rugby players (72 males, 30 females; aged 15–21), divided into 34 groups of three. Data collection took place across nine sessions conducted in the training facilities of high-performance rugby centers in France, involving either male or female players within a given session. During each session, teams of three attackers were constituted by the coaching staff to ensure comparable playing levels and representative profiles (*i.e.*, balancing forwards and backs).

### 2.2. Experimental task and protocol

The task consisted of a rugby union small-sided game on a 20x15m field, in which a team of three attackers (*i.e.*, A1, A2, A3) played against a team of three defenders (*i.e.*, D1, D2, D3). Each team completed 24 offensive trials, in different conditions based on the manipulation of the two independent variables: two defense scenarios were designed to manipulate task complexity (LC: low complexity; HC: high complexity); two types of motivational goals were primed to manipulate social identity (TG: team-oriented goal; SG: self-oriented goal). Trials were performed in blocks of 12, corresponding to one motivational goal condition, with defense scenarios randomized and player roles semi-randomized within each block. For motivational goals, the session was presented as consisting of a pair of tests – one about individual performance and the other about collective performance – and motivational goals were reminded to the attacking players before each block of trials. For defense scenarios, the initial position of the three defenders was different: two specific configurations were designed to create different gaps in the defense, while sharing the same initial setup so that attackers could not anticipate the scenario ([Fig. 1](#)). To ensure the ecological validity of the task, these two scenarios were designed by expert rugby coaches as samples of a real rugby union game. Previous work confirmed that the HC situation significantly increased the uncertainty of the first



**Fig. 1.** Illustration of the two defense scenarios.

Note. The field measured 20 m in length and 15 m in width, the arrow representing the way of attack. The triangles represent the cones that were placed on the field to indicate to the attackers (A1, A2, A3) and the defenders (D1, D2, D3) their respective initial position. The cones were placed at: 5 m and 15 m in length; 2.5 m, 7.5 m and 12.5 m in width. The dashed line represents the midline of the field along its width, that was marked on the field to indicate to the defenders the mid-line they could not cross. The letter “C” represents coach position, who gave verbal signals (*i.e.*, “ready”, “go”) and initiated trials by passing the ball to A1. The high complexity (B.) and low complexity (C.) scenarios started from the same initial position (A.) so that attackers did not know the scenario before it started. Each scenario involved two defenders in the front line and one in the back line, and the difference in terms of “complexity” was mainly due to the gap between the two front-line defenders in the low complexity scenario.

ball carrier's decision-making compared to the LC, and that the goal priming significantly influenced players' psychological states, with TG provoking a stronger activation of social identity than SG (Hacques et al., 2025).

### 2.3. Data collection

All trials were filmed using a high-definition camera and videos were then annotated to capture information about passes and receptions (*i.e.*, timecode, player identities), and about the end of each trial (*i.e.*, timecode, outcome) – the start of each trial being defined as the reception of the ball by A1. Additionally, all players wore GPS devices, so the video annotations were synchronized with players' spatiotemporal movements.

### 2.4. Modeling interpersonal coordination

A research framework diagram illustrates the analytical workflow of this study, from the experimental constraints to the data-processing steps for modeling team coordination patterns and player roles within it (Fig. 2).

First, a passing network approach was used to evaluate coordination patterns employed by a team, as proposed in Passos et al. (2011). Each trial was represented as a passing network in which nodes correspond to players (*i.e.*, A1, A2, A3) and edges to successful passes between them. First, the network corresponding to each trial was reduced to a *graphlet* (Fig. 3), defined as a directed small graph ignoring players' identity (Bourgeois et al., 2024).

For graphlet analyses as for all subsequent analyses, data were aggregated across teams, because team-level analyses would have resulted in an insufficient number of trials per condition. Also, only the successful trials were taken into account, to ensure the comparability of passing networks (*i.e.*, comparing only passing networks sharing the same start and end). Overall, successful trials represented 60.8% of the trials (Hacques et al., 2025). Among the unsuccessful trials that were excluded, 74.0% corresponded to graphlet "1" or graphlet "12", thus involving at most one successful pass (Appendix 1). Consequently, excluding these trials predominantly removed very simple coordination patterns and allowed a focus on richer patterns.

In this context, graphlets therefore represent the coordination patterns used by teams to succeed in the task. But graphlets miss an important feature of interpersonal coordination that is expected to be affected by the experimental constraints: the spatial dimension. Thus, *ball trajectories* were reconstructed from the start to the end of each trial, combining event data with positional data. These trajectories provided a continuous representation of how the ball moved through space during successful trials. Specifically, the ball was considered as either being carried by a player moving in a rectilinear uniform motion from the ball-passing point (*i.e.*, timing and location of the pass event) to the ball-receiving point (*i.e.*, timing and location of the reception event). Ball trajectories offer a first global visualization of how teams collectively used the spatial dimension during their trials.

Accordingly, to capture player roles within team coordination patterns, information relative to their topological involvement (*i.e.*, a player's position within the graphlet) and the spatial dimension of their actions (*i.e.*, the location of ball-passing events on the field) were integrated into the graphlets. Thus, the definition of graphlet was extended in order to include both information, inspired by extensions that have been done in a comparable framework – namely, the flow motifs introduced in Gyarmati et al. (2014) – and by the concepts of *flow centrality* and *flow betweenness* defined in Korte et al. (2019) for passing networks. On the one hand, for the topological part, a distinction was made between "being involved in" (*i.e.*, centrality) and "also being intermediary in" (*i.e.*, betweenness) the passing sequence. These role-sensitive graphlets are hereafter referred to as *oriented graphlets* (Fig. 4). On the other hand, for the spatial part, a discretization of space

and time was performed to allow the continuous ball trajectories to be represented within a discrete graphlet-based framework. Thus, only the ball-passing and ball-receiving points were retained from ball trajectories, and a  $4 \times 3$  grid was created to divide the field into 12 equal zones (*i.e.*, 5 m length and 5 m width each) named  $Z_1$  to  $Z_{12}$  (Fig. 5). This spatial segmentation creates three corridors across the width of the field, aligning with the initial positions of attackers, while also accounting for depth, as the initial positions of defenders were structured in two lines. At this stage, *event-player matrices* were computed, accounting for the number of events (*i.e.*, passes, receptions), in each zone of the field, for each player (*e.g.*, matrix of passes for player A1, matrix of receptions for player A3). Thus, it provided a discretized representation of player roles, accounting for their use of space.

Finally, the combination of the 12 field zones with oriented graphlets resulted in 2-dimensional matrices (*i.e.*, oriented graphlet in columns, field zones in rows) that were produced for a given player (*i.e.*, A1, A2, A3) and a given event (*i.e.*, pass, reception). More specifically, these matrices were built with an iterative approach: it started with an empty matrix (full of zeros); for each occurrence of a given event by a given player, both the information relative to the oriented graphlet and the field zone in which it occurred were retained; the value of the associated matrix cell was incremented by 1. At the end, each cell of the matrix contained the number of occurrences of a given event performed by a given player in a given zone on the field and for a given oriented graphlet (Table 1). Such matrix, hereafter referred to as *spatialized oriented graphlet matrix* (or SOG matrix), constituted the final unit of analysis of the present work: it described player roles within coordination patterns by capturing how and where they were involved in which passing patterns.

### 2.5. Statistical procedure

According to the initial hypothesis, greater differences in interpersonal coordination were expected between TG and SG conditions in the HC situation than in the LC situation.

Graphlet occurrences were analyzed using multinomial logistic regression models, using the "nnet" R package. Different nested models were computed and compared using likelihood-ratio tests based on  $\chi^2$  statistics. In these models, graphlet type was modeled as a categorical response variable, graphlet counts were used as weights, and eventually motivational goals, defense scenarios, and their interaction as predictors. Practically, these models were therefore fitted on aggregated graphlet counts for combinations of experimental conditions, such that the response variable captured the relative frequency distribution of graphlet types within each condition. Accordingly, it tested whether the probability of observing a given graphlet type varied as a function of the factors included. First, a full model (*i.e.*, including the two main effects and the interaction effect) was compared to a baseline model including only an intercept (*i.e.*, not including any main effects or interaction effect) which represents the null hypothesis of identical graphlet distributions across experimental conditions. Then, the relative contribution of each experimental factor was examined by comparing the full interaction model to reduced models including only one factor (*i.e.*, main effect of either motivational goals or defense scenarios). Here, likelihood-ratio tests evaluated whether adding the second factor and its interaction with the first improved model fit, thereby indicating which experimental manipulation accounted for the observed differences in graphlet distributions. Specifically, a significant likelihood-ratio test indicates that including the second experimental factor significantly improves the fit of the model. In practical terms, each graphlet represents a specific temporal pattern of interactions between players during a trial: detecting differences in graphlet distributions would therefore reflect that team used different patterns under the different experimental conditions.

Additionally, in line with the concept of degeneracy in complex adaptive systems, entropy-based metrics were specifically chosen to

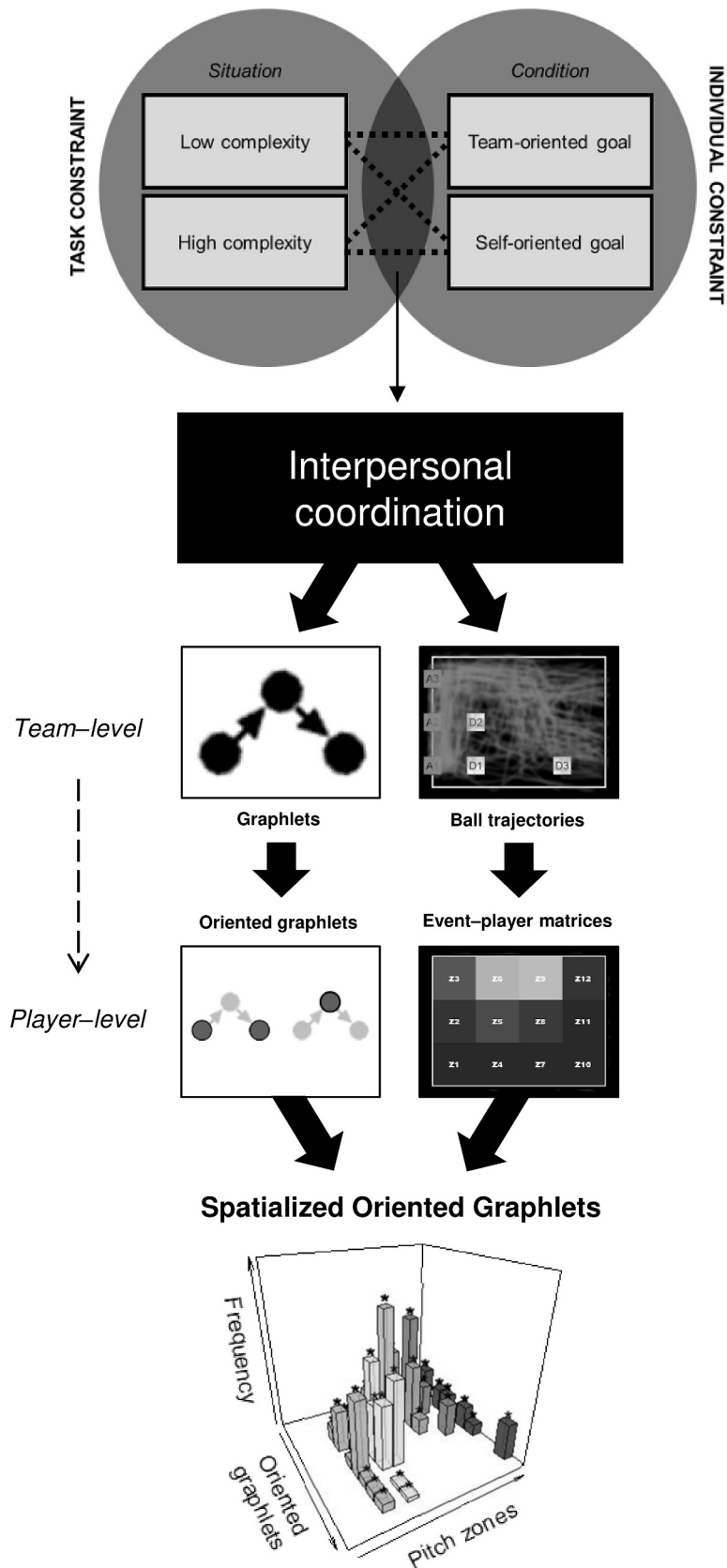
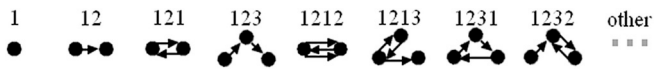


Fig. 2. Analytical workflow.

Note. The figure summarizes the research framework linking experimental constraints to interpersonal coordination outcomes. The upper part illustrates that a task constraint and an individual constraint were manipulated to study their combined effect on interpersonal coordination. The lower part illustrates how interpersonal coordination was modeled, at team-level (*i.e.*, coordination patterns) and at player-level (*i.e.*, roles within it), by combining topological and spatial information at both scales.



**Fig. 3.** List of all graphlets.  
Note. Numbers in graphlet names reflect successive ball carriers' order.

capture the diversity of functional solutions through which the task has been achieved (Tononi et al., 1999). Thus, the level of entropy of each distribution was calculated based on the classical definition of entropy for a distribution (Shannon, 1948) (Definition 1). In this context, entropy informed on the behavioral diversity in team coordination patterns: higher entropy values indicate that teams relied on a more diverse

set of coordination patterns to achieve the task, whereas lower entropy values indicate that teams relied on a smaller and more stereotyped set of coordination patterns (Bourgeois et al., 2024).

**Definition 1.** Let  $S_G$  denote the entropy for one graphlet distribution.  $S_G$  is defined as follows:

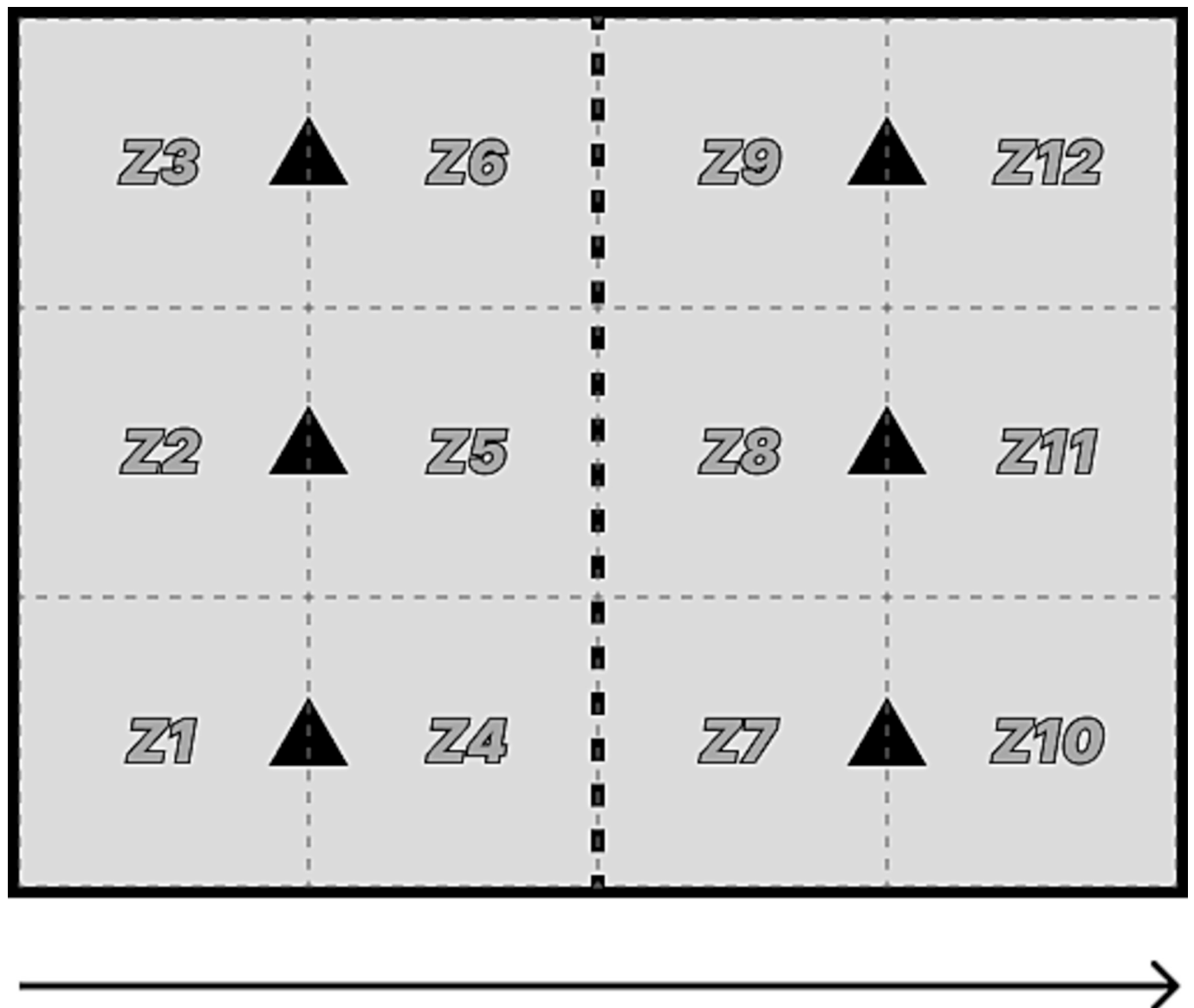
$$S_G = - \sum_{i=1}^N p_i \log_2(p_i)$$

where  $p_i$  is the probability of graphlet  $i$ , and  $N$  is the total number of possible graphlets.

Ball trajectories were aggregated for each combination of the two



**Fig. 4.** List of all oriented graphlets.  
Note. The letter “B” (Betweenness) means that the player is an intermediary node within the graphlet (i.e., a node in-between two other nodes); The letter “C” (Centrality) means that the player is a node within the graphlet, but not an intermediary one. The “B” and “C” nodes are respectively highlighted in red within their corresponding oriented graphlets. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)



**Fig. 5.** Illustration of the 12 field zones ( $Z_1$  to  $Z_{12}$ ).

**Table 1**  
Example of spatialized oriented graphlet matrix, for the receptions of player A3 in the CG–LC condition.

ZONE	1_C	12_C	121_C	121_B	123_C	123_B	1212_B	1213_C	1213_B	1231_C	1231_B	1232_C	1232_B	other_C	other_B
Z1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Z2	0	0	0	1	0	1	0	0	0	0	1	0	1	0	0
Z3	0	17	0	10	1	15	0	0	1	0	17	0	10	0	6
Z4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Z5	0	0	0	0	1	0	0	0	0	0	1	0	0	0	1
Z6	0	0	0	0	1	6	0	0	0	0	3	0	1	0	0
Z7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Z8	0	0	0	0	2	0	0	0	0	0	0	0	1	0	1
Z9	0	3	0	0	2	0	0	1	0	0	0	0	2	0	0
Z10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Z11	0	1	0	0	1	0	0	0	0	0	0	0	0	0	0
Z12	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1

Note. In that example, each cell contained the number of receptions performed by player A3 in a given zone on the field (row) and for a given oriented graphlet (column). For example: this SOG matrix reveals that, for the CG–LC condition, most of A3 ball-receiving events occurred in Z<sub>3</sub> (i.e., 77 times over the 113 total trials), and that his main topological roles were either being intermediary within graphlet 123 or 1231 (i.e., 21 times in 123\_B and in 1231\_B).

independent variables, and their visualization was used to evaluate differences through pairwise comparisons. The evaluation of which experimental factor was associated with the largest differences in terms of ball trajectories was performed by contrasting them across one experimental factor (i.e., HC vs. LC for a given motivational goal, or SG vs. TG within a given defense scenario), which also allowed the interaction between the two factors to be examined. In addition, a more detailed comparison based on trajectory densities was performed to provide a quantitative assessment of the visual differences (Appendix 2).

Event–player matrices were also computed for each combination of the two independent variables, and the Earth Mover’s Distance (EMD) metric (Rubner et al., 2000) was used in order to quantify the differences between these matrices. Compared to other classical metrics for measuring distances between matrices, EMD is particularly suitable in the case of such spatial data: it quantifies the minimal “work” required to transform one spatial distribution into another by accounting for the cost of transporting “mass” across space, thus considering the underlying geometry (Girela, 2019). This metric has already been shown to be sensitive and meaningful in the context of team sports (Gómez-Jordana et al., 2021). In this context, EMD therefore provided a quantitative measure of differences in players’ roles based on the spatial distribution of their actions: larger EMD values indicate greater differences in how players occupied space and distributed their actions across the field, whereas smaller values indicate more similar spatial roles across conditions. Pairwise comparisons were performed to examine which experimental factors were associated with the largest differences for which event–player matrices. Because event–player matrices were computed on data aggregated across teams, confidence intervals associated with EMD values could not be derived directly. To address this, an empirical subsampling procedure was employed. At each iteration, 10% of events were randomly removed within each cell of each event–player matrix, and EMD was recomputed. This was repeated 1000 times, yielding empirical distributions of EMD values from which 95% intervals were derived. In this context, confidence intervals were used to evaluate the robustness (i.e., stability to moderate random perturbations of the data) of the observed differences in terms of EMD across experimental conditions, thereby supporting the descriptive assessment of the influence of the experimental factors. Specifically, for each pairwise comparison, differences between conditions could not be considered as

robust if the empirical 95% interval of the EMD overlapped with the corresponding interval of the contrasted condition. Conversely, non-overlapping confidence intervals indicate that the detected difference is structurally embedded in the data and not sensitive to minor fluctuations within the data.

Finally, SOG matrices were computed for each combination of the two independent variables and were compared based on their level of entropy, calculated using an extension of the first definition. Specifically, the classical definition of entropy for a distribution was first used for each oriented graphlet (i.e., for a column), then weighted by the number of graphlets (i.e., sum of the column), and finally summed up (Definition 2). Thus, the entropy of a SOG matrix corresponds to the sum of the entropies of each oriented graphlet, weighted by their frequency. In this context, it informed on the degree of flexibility or specialization of a player’s role: high entropy values indicate a flexible role, that is involved in a broader variety of coordination patterns, whereas low entropy values indicate a specialized role, involved in a narrower and more stereotyped set of coordination patterns (Bourgeois et al., 2025). Here again, confidence intervals could not be derived directly: a subsampling procedure was implemented to evaluate the robustness of the entropy measures. At each iteration, 10% of both matrix dimensions were randomly omitted (i.e., one field zone and one oriented graphlet category) and entropy recomputed. This procedure was repeated 1000 times, and the resulting empirical distributions of entropy values were used to derive 95% confidence intervals. In this context, these intervals quantify how stable the entropy estimates (and associated contrasts) remain under moderate perturbations of the matrix representation, and can therefore be used to identify entropy differences that reflect stable adaptations of player roles to task and individual constraints. Specifically, for each player and event type, the main effect of task complexity was defined as the average entropy difference between HC and LC situations across motivational goals, while the main effect of motivational goals was defined as the average entropy difference between SG and TG across defense scenarios. In addition, an interaction contrast was computed as a difference-of-differences between these two factors. Contrasts whose empirical confidence intervals excluded zero were interpreted as robust to perturbation, whereas contrasts whose intervals included zero were interpreted as lacking robustness (either reflecting a similarity between conditions or differences that are not preserved

under perturbation). Overall, this approach evaluated how task complexity and motivational goals modulate player roles by identifying stable tendencies in their involvement in team coordination patterns.

**Definition 2.** Let  $S_{OG}$  denote the entropy for one oriented graphlet, and  $S_{SOGM}$  the entropy of spatialized oriented graphlet matrix. These entropies are defined as follows:

$$S_{OG} = - \sum_{z=1}^{Zn} p_z \log_2(p_z)$$

$$S_{SOGM} = - \sum_{OG=1}^{OGn} P_{OG} S_{OG}$$

where  $p_z$  is the probability of field zone  $z$  and  $p_{OG}$  is the probability of oriented graphlet  $OG$ ;  $Zn$  is the total number of field zones and  $OGn$  is the total number of oriented graphlets.

### 3. Results

#### 3.1. Graphlets

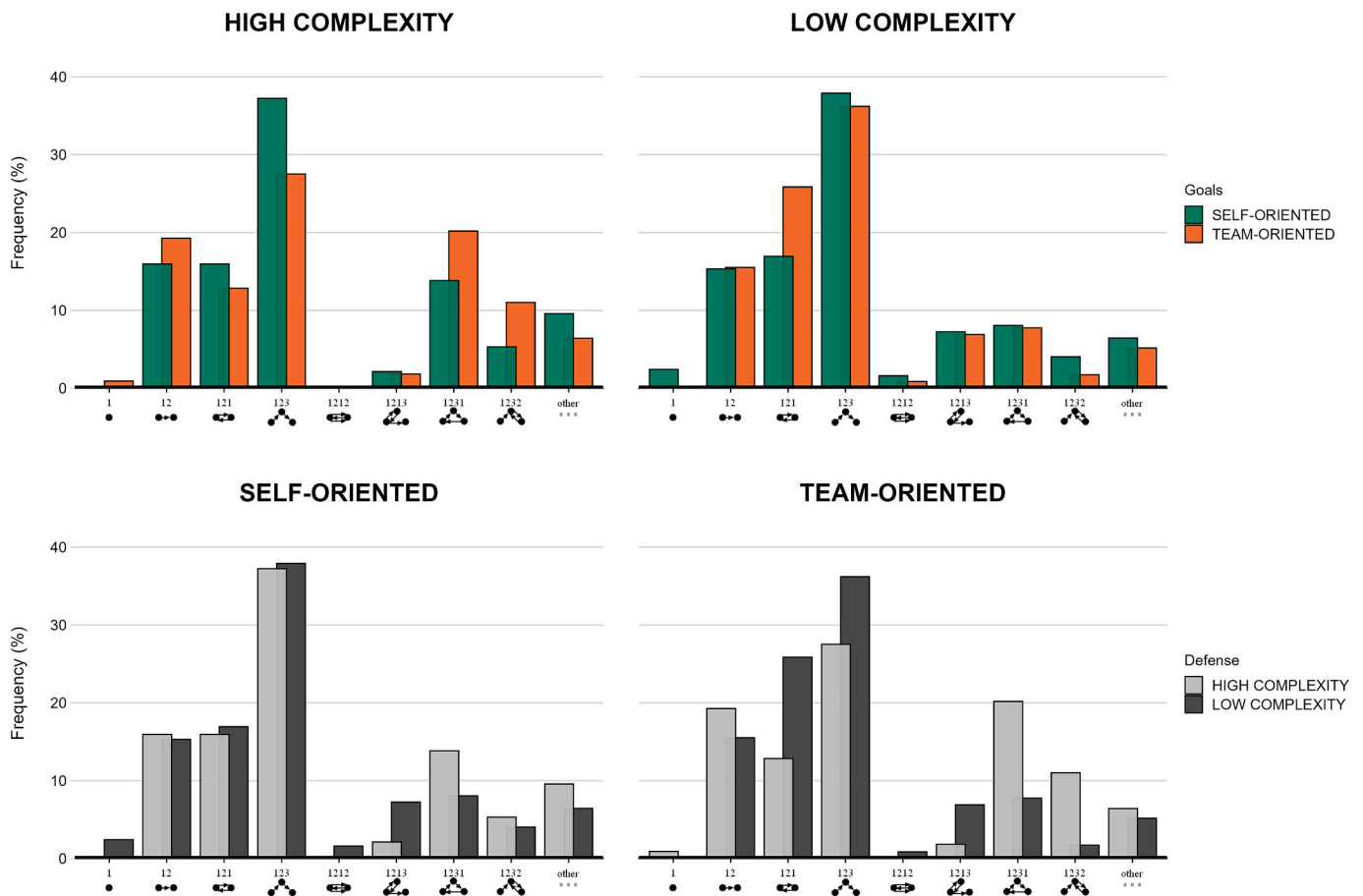
The multinomial logistic regression models analysis revealed that the distribution of graphlets was significantly affected by experimental conditions (Fig. 6). Specifically, the full model provided a significantly better fit than the baseline model, indicating that the experimental constraints influenced the overall distribution of team coordination patterns ( $\chi^2(24) = 45.04, p = .006$ ). Also, model comparisons further showed that adding defense scenarios (and their interaction with

motivational goals) significantly improved model fit relative to a model including motivational goals only ( $\chi^2(16) = 39.53, p < .001$ ), whereas adding motivational goals (and their interaction with defense scenarios) did not improve model fit relative to a model including defense scenarios only ( $\chi^2(16) = 15.13, p = .52$ ). This result indicates that the observed effect was primarily driven by defense scenarios, while there was no evidence that motivational goals, either as a main effect or through an interaction effect, provided additional explanatory power for graphlet distributions.

The entropy associated with the distribution of graphlets corresponding to each combination of the two independent variables revealed relatively large values, ranging from 2.39 to 2.61 (i.e., TG–HC: 2.59, 82%; TG–LC: 2.39, 75%; SG–HC: 2.44, 77%; SG–LC: 2.61, 82%). These values correspond to 75%–82% of the maximal theoretical entropy, that is around 3.17 for a uniform distribution across nine categories.

#### 3.2. Ball trajectories

The visualization and visual comparisons of ball trajectories for each combination of the two independent variables revealed a notable effect of defense scenarios: trajectories in HC and LC situations were considerably different, in both motivational goal conditions (Fig. 7). In contrast, no such effect of motivational goals could be observed: trajectories in SG and TG conditions appeared to be visually similar, in both defense scenario situations. This pattern was confirmed by the density analysis, conducted on a shared scale (Appendix 2).



**Fig. 6.** Comparison of graphlet distributions according to motivational goals and defense scenarios.

Note. Each panel provides a comparison of graphlet frequencies: upper panels compare motivational goals for a given defense scenario; lower panels compare defense scenarios for a given motivation goal. According to the results, only the defense scenario significantly affected the graphlet distribution.

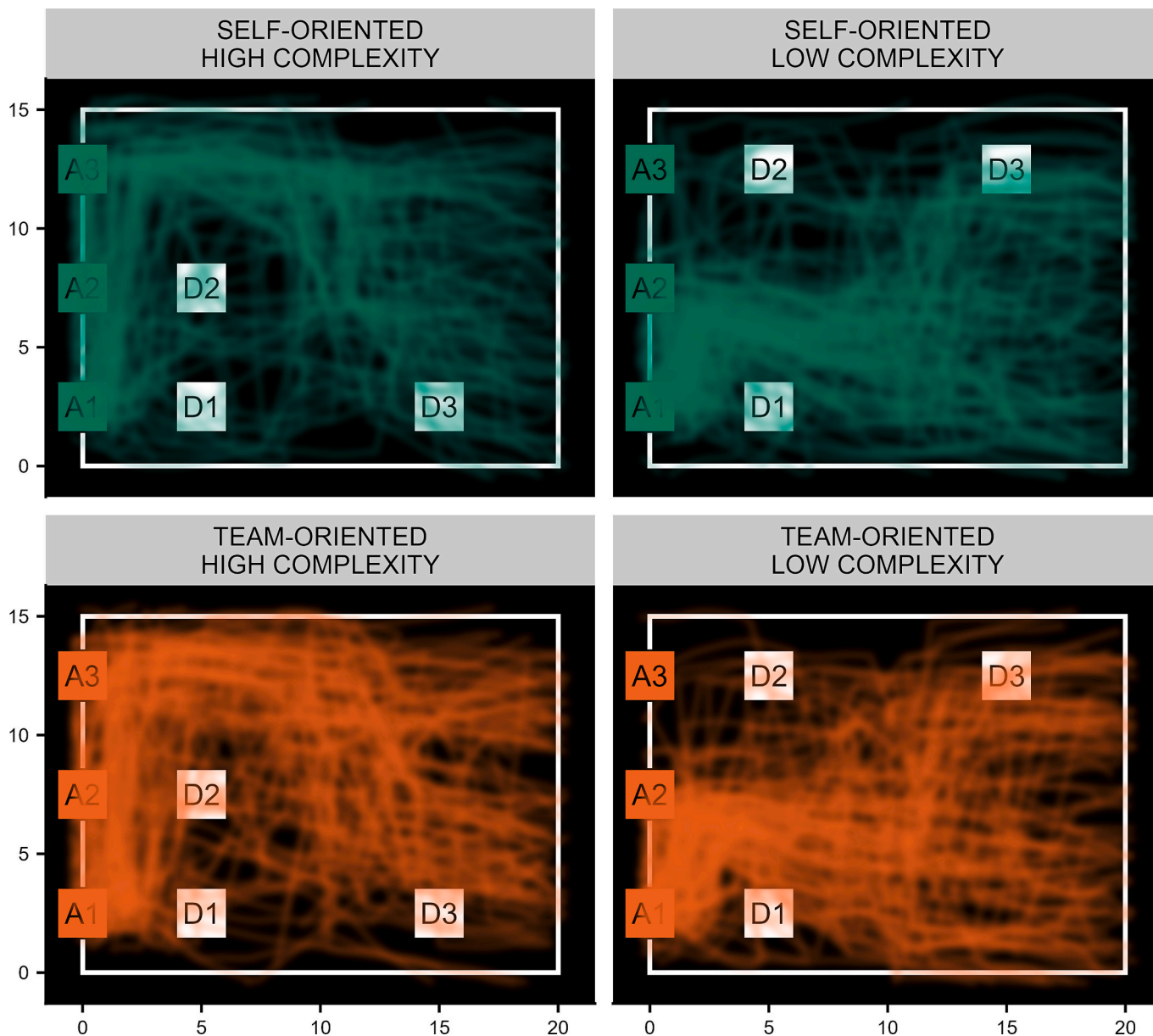


Fig. 7. Visualization of ball trajectories according to motivational goals and defense scenarios.

Note. As each panel corresponds to a combination of a motivational goal and a defense scenario, several comparisons are relevant: left/right comparisons to evaluate the effect of defense scenarios, top/bottom comparisons to evaluate the effect of motivational goals. Visually, it is clear that left/right comparisons show distinct trajectories, whereas top/bottom comparisons reflect more similar trajectories.

### 3.3. Event-player matrices

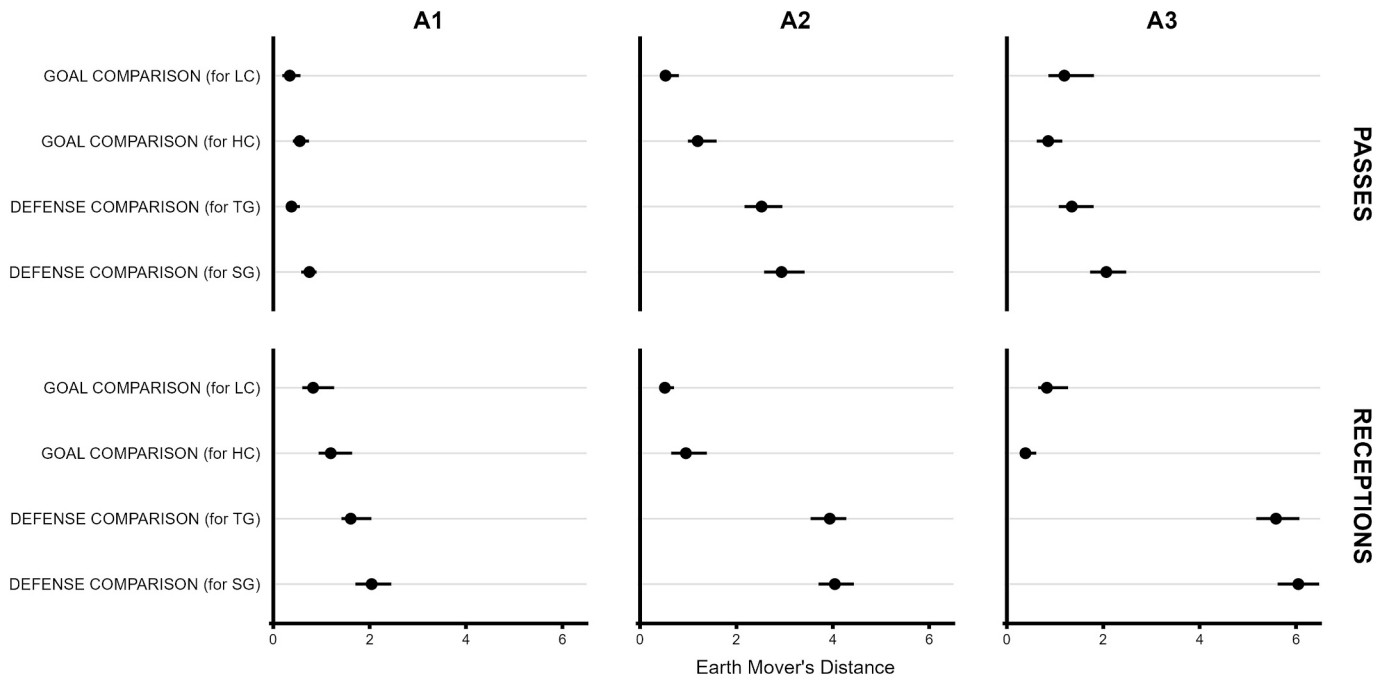
Overall, pairwise comparisons of event-player matrices using EMD confirmed that defense scenarios had a greater influence on the spatial dimension of players' actions than the motivational goals. Indeed, the magnitude of the EMD values and their associated empirical confidence intervals derived from the subsampling procedure revealed that the largest distances were obtained when contrasting defense scenarios than when contrasting motivational goals (Fig. 8, Appendix 3). Still, player- and event-dependent magnitudes were identified. The greater distances appeared for, in that order: receptions of player A3 (in SG condition: EMD = 6.05, 95% CI [5.62; 6.48]; in TG condition: EMD = 5.58, 95% CI [5.17; 6.07]), receptions of player A2 (in SG condition: EMD = 4.04, 95% CI [3.70; 4.44]; in TG condition: EMD = 3.94, 95% CI [3.54; 4.28]), passes of player A2 (in SG condition: EMD = 2.92, 95% CI [2.57; 3.41]; in TG condition: EMD = 2.52, 95% CI [2.17; 2.95]). For these contrasts,

no interaction effect was observed, since the values corresponding to SG and TG conditions showed overlapping empirical 95% confidence intervals. This result indicates that the spatial differences were not robustly modulated by motivational goals. In contrast to A3 and A2, player A1's role appeared to be less affected, by either experimental factor. All event-player matrices are displayed to provide further qualitative interpretations (Appendix 3).

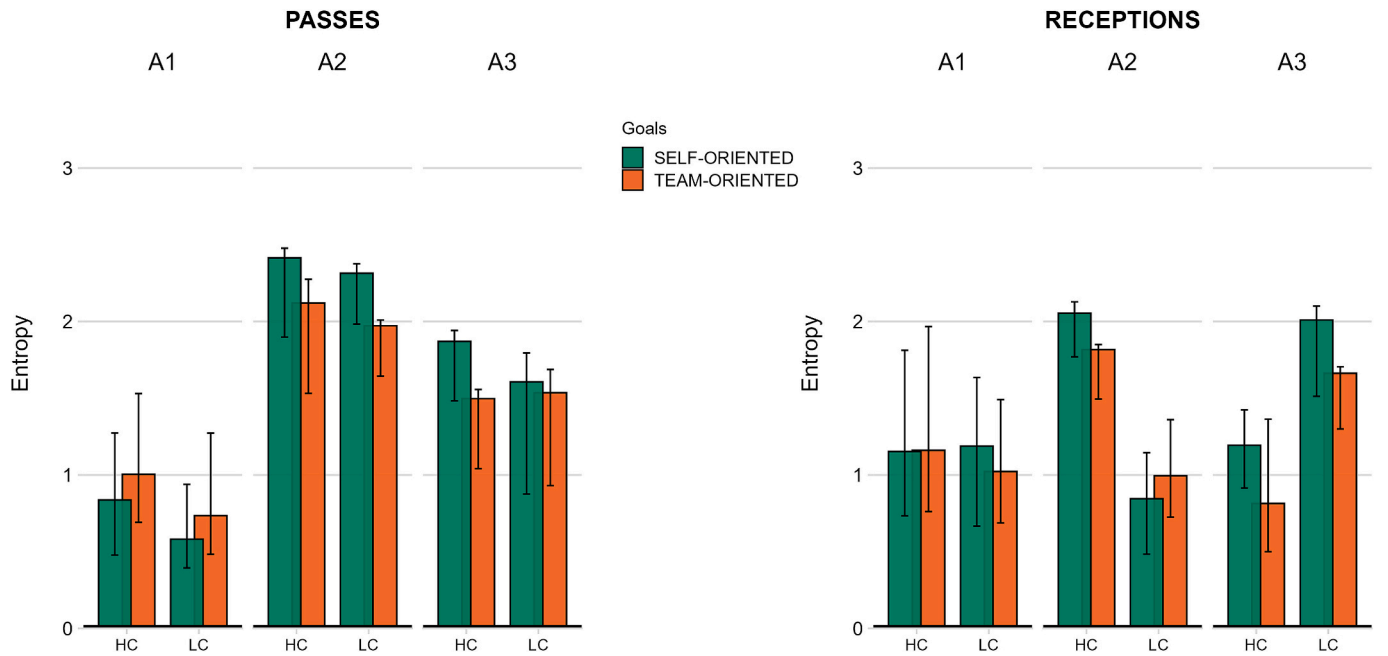
### 3.4. Spatialized oriented graphlets

The entropy level associated to SOG matrices showed player- and event-dependent variations across experimental factors (Fig. 9), with several differences that remained stable to data perturbation across the subsampling procedure – thus revealing robust contrasts (Table 2).

Player A2 exhibited higher entropy in the HC situation compared to the LC situation (mean = 0.95, 95% CI [0.67; 1.19]), whereas player A3



**Fig. 8.** Distance between event–player matrices according to motivational goals and defense scenarios. Note. For a given comparison of two event–player matrices, the point corresponds to the original EMD value computed, and the error bar to the 95% CI obtained via the subsampling procedure. Larger EMD values indicate greater differences between matrices, allowing identification of which contrasts show the largest differences and thus which factor has the greatest impact (*i.e.*, defense scenario comparison or motivational goal comparison). Potential interaction effects can be examined by comparing similar contrasts across conditions (*e.g.*, defense comparisons for TG vs. SG condition). Here, all confidence intervals across such contrast comparisons are overlapping, indicating that no robust interaction effect can be observed.



**Fig. 9.** Entropy in spatialized oriented graphlet matrices according to motivational goals and defense scenarios. Note. Entropy values were computed on original SOG matrices for the combination of both experimental factors (*i.e.*, defense scenarios and motivational goals), while error bars represent the 95% CI obtained via the subsampling procedure. Higher entropy values indicate a more flexible role, whereas lower values indicate a more specialized role. Comparing overlapping bars of different colors reflects the effect of motivational goals within a given defense scenario, while left/right comparisons of bars with the same color reflect the effect of defense scenarios for a given motivational goal. Interaction effects were evaluated through contrast analyses; those whose 95% confidence intervals exclude zero were deemed robust. Here, robust interaction effects were observed for receptions of A2 and passes of A3.

exhibited higher entropy in the LC situation compared to the HC situation (mean = 0.76, 95% CI [0.42; 0.98]). This result indicates that defense scenarios influenced the roles of players A2 and A3, specifically

through changes in the diversity of their ball-receiving actions. However, no robust effect of defense scenarios was observed for A1 actions, nor for the ball-passing actions for any player.

**Table 2**

Robustness test for entropy contrasts in spatialized oriented graphlet across experimental factors.

Effect	Event–player	Estimate	95% CI	Interpretation
Defense scenarios	Passes–A1	0.24	[–0.01; 0.43]	Not robust
	Passes–A2	0.13	[–0.10; 0.37]	Not robust
	Passes–A3	0.11	[–0.18; 0.79]	Not robust
	Receptions–A1	0.07	[–0.15; 0.35]	Not robust
	<b>Receptions–A2</b>	<b>0.95</b>	<b>[0.67; 1.19]</b>	<b>Robust</b>
	<b>Receptions–A3</b>	<b>–0.76</b>	<b>[–0.98; –0.42]</b>	<b>Robust</b>
Motivational goals	<b>Passes–A1</b>	<b>0.16</b>	<b>[0.07; 0.29]</b>	<b>Robust</b>
	<b>Passes–A2</b>	<b>–0.31</b>	<b>[–0.51; –0.01]</b>	<b>Robust</b>
	<b>Passes–A3</b>	<b>–0.23</b>	<b>[–0.37; –0.09]</b>	<b>Robust</b>
	Receptions–A1	–0.06	[–0.13; 0.02]	Not robust
	Receptions–A2	–0.04	[–0.12; 0.05]	Not robust
	<b>Receptions–A3</b>	<b>–0.33</b>	<b>[–0.46; –0.22]</b>	<b>Robust</b>
Interaction	Passes–A1	–0.01	[–0.15; 0.21]	Not robust
	Passes–A2	–0.06	[–0.60; 0.49]	Not robust
	<b>Passes–A3</b>	<b>0.31</b>	<b>[0.05; 0.67]</b>	<b>Robust</b>
	Receptions–A1	–0.18	[–0.36; 0.11]	Not robust
	<b>Receptions–A2</b>	<b>0.38</b>	<b>[0.21; 0.55]</b>	<b>Robust</b>
	Receptions–A3	0.01	[–0.49; 0.46]	Not robust

Note. The contrasts reported are  $HC - LC$  for main effects of defense;  $SG - TG$  for main effects of motivational goals; and  $(LC, SG - LC, TG) - (HC, SG - HC, TG)$  for interaction effects. A contrast was considered “robust” (in bold) when its 95% confidence interval did not include zero.

For ball-passing actions, players A2 and A3 exhibited higher entropy in the SG condition compared to the TG condition (A2: mean = 0.31, 95% CI [0.01; 0.51]; A3: mean = 0.23, 95% CI [0.09; 0.37]), whereas A1 exhibited higher entropy in the TG condition compared to the SG condition (mean = 0.16, 95% CI [0.07; 0.29]). This result indicates that motivational goals also influenced player roles, although to a lesser extent than defense scenarios. However, these effects should be interpreted with caution, as several confidence intervals were close to including zero, indicating limited robustness of these contrasts. In fact, only the effect on ball-receiving actions of player A3 appeared robust, with higher entropy in the SG condition compared to the TG condition (mean = 0.33, 95% CI [0.22; 0.46]), indicating a stable increase in the diversity of the role of player A3 when pursuing a team-oriented motivational goal.

Interaction effects were robust for two contrasts: for the ball-receiving actions of player A2 (mean = 0.38, 95% CI [0.21; 0.55]), and for the ball-passing actions of player A3 (mean = 0.31, 95% CI [0.05; 0.67]). This result indicates that the influence of motivational goals on A2 and A3 role depends on the defense scenario. On the one hand, for A2 receptions, the observed entropy values showed an inversion of the motivational goals' effect across defense scenarios: in the HC situation, the TG condition was associated with higher entropy than the SG condition ( $TG-SG = 0.24$ ); in the LC situation, the SG condition was associated with higher entropy than the TG condition ( $TG-SG = -0.15$ ). On the other hand, for A3 passes, the interaction only reflected a change in the magnitude of the motivational goals' effect: the entropy difference between TG and SG was more pronounced in the HC situation ( $TG-SG = 0.37$ ) than in the LC situation ( $TG-SG = 0.07$ ), indicating a greater diversity in the TG condition for the HC situation. Two visualizations of spatialized oriented matrices are proposed and displayed to provide further qualitative interpretations (Appendix 4).

## 4. Discussion

### 4.1. Effect of the task constraint: task complexity

Overall, the manipulation of experimental constraints affected team coordination patterns, as evidenced by the initial analysis of passing network structures. The main observation is that differences in graphlet distributions were primarily driven by the defenders' initial positions, rather than by attackers' motivational goals – or by their interaction. However, it did not seem to translate into differences in entropy, indicating that differences lied in the nature of the coordination patterns rather than in their diversity. A closer examination reveals that simpler graphlets (e.g., “121” or “123”) tended to be more frequent in the low complexity situation, whereas more complex ones (e.g., “1231” or “1232”) appeared more often in the high complexity situation. A possible interpretation for this finding is that teams may need to employ more complex coordination patterns to perform more complex tasks. Moreover, the observed entropy values indicate that teams relied on a diverse set of graphlets to successfully achieve the task, with entropy levels reaching high levels of the theoretical maximum. From a theoretical standpoint, such diversity in team coordination patterns may reflect a substantial exploitation of the degeneracy property (Seifert et al., 2016) and further supports the conceptualization of sport teams as complex adaptive systems (Davids, 2014).

This strong effect of the task constraint on team coordination patterns also appeared in the way the spatial dimension was exploited, as illustrated by the comparison of ball trajectories. As expected, in the less complex task, the gap between the two front defenders has been used by the attackers to cross the first defensive line. In contrast, in the more complex task, players had to pass the ball laterally to create a gap which affords crossing the first defensive line. Thus, present results appeared consistent with the idea that defense spatial configuration can affect attacking players' behavior by shaping their landscape of available affordances, particularly through the presence of gaps between front defenders – as shown in Correia et al. (2012).

This spatial reorganization was reflected at the level of player roles, as there were stable tendencies in the way defense scenarios affected the spatial roles of players A2 and A3 – particularly for their ball-receiving actions. Furthermore, when topological information was integrated to fully characterize these roles, the entropy analyses of spatialized oriented graphlet matrices showed that this effect could be described in terms of role flexibility or specialization: specifically, the roles of A2 and A3 were each more diversified in one of the two defense scenarios, indicating that their involvement in team coordination patterns adapted to defenders' initial positions. In contrast, the role of player A1 in team coordination patterns remained consistently specialized across defense scenarios.

### 4.2. Interaction with the individual constraint: social identity

Priming team-oriented goals was expected to activate players' social identity (Campo, Champely, et al., 2019), which would in turn make players more sensitive to actions possibilities relevant to their team (Weichold & Thonhauser, 2020). Although to a lesser extent than defense scenarios, stable tendencies in how motivational goals influenced player roles were observed. For ball-passing actions, it seems that team-oriented goals increased the flexibility of A1's role, whereas they were associated with more specialized roles for A2 and A3.

More fundamentally, while goal priming alone was less influential than task complexity alone, both constraints appeared to interact to shape interpersonal coordination. There was no evidence of an interaction effect on team coordination patterns, but stable tendencies did emerge at the level of player roles. On the one hand, an evolution of A3's role across experimental constraints appeared to be consistent with this hypothesis, as the effect of goal priming was more pronounced in the more complex task, and indicated a more specialized role when pursuing

team-oriented goals. With regard to the theory of collective affordances (Weichold & Thonhauser, 2020), this could be interpreted as meaning that priming self-oriented goals created a conflict with team expectations and, in turn, introduced greater variability in how A3 responded to the task – an effect that emerged primarily in a task complex enough to offer him multiple action possibilities. In contrast, with the priming of team-oriented goals, a greater attunement to action possibilities that are relevant for the team as a whole could have resulted in a more consistent behavior of A3. This also closely aligns with the results reported in Hacques et al. (2025) for A1's decision-making, where team- *versus* self-oriented goals were respectively associated with a higher frequency of passing *versus* running actions. On the other hand, the interaction observed for A2 did not follow the initial hypothesis, yet it appeared even more pronounced. Rather than reflecting a simple difference in magnitude, it corresponds to a qualitative change in the nature of the role: the effect of motivational goals on role specialization seems to shift across defense scenarios.

#### 4.3. Contributions, limits and perspectives

Previous work demonstrated that the constraint manipulation was effective, both for the task and individual constraints, and that it affected the diversity of the first ball-carrier's behavior (Hacques et al., 2025). But the choices of this player are also a consequence of his teammates' actions, that fall within his landscape of affordances. In other words, A1's behavior also reflects the roles assumed by A2 and A3 within team coordination patterns. Thus, the present work extended the analytical focus from A1's decision-making to interpersonal coordination. The findings revealed that teams adapted their coordination patterns to task complexity, along with adjustments in player roles, and that social identity indeed interacted with task complexity to influence A2 and A3 roles. The presence of interaction effects highlights the importance of considering motivational and social context when analyzing interpersonal coordination. In particular, it may participate in shaping the functional distribution of roles, even if the global structure appears stable. However, it is to be considered with caution given that the statistical tests were not designed to provide strong inferential power and could not provide evidence of statistical significance. Actually, only robustness analyses of the observed differences were performed, indicating whether a tendency remains stable under random perturbations within data.

Consistent with a constraint-led approach (Renshaw & Chow, 2019), this work emphasizes that manipulating task constraints in small-sided games can structure players' landscape of available affordances, with direct consequences for players' interactions. It also supports that a goal-priming procedure can activate social identity (Campo, Champely, et al., 2019), and that it can function as a constraint on individuals. More precisely, the activation of social identity processes may be seen as a constraint with limited effects on interpersonal coordination on its own, but which can exert an influence on player roles within team coordination patterns through its interaction with task complexity. Thus, these findings open the possibility of deliberately manipulating social identity in practice contexts to influence the emergence of interpersonal behaviors, and that goal-priming procedures may serve as a practical means to achieve this.

However, the scope of these implications must be tempered. First, it should be noted that the observations on team coordination patterns and player roles are specific to the small-sided game used in this study. Although the task was designed by expert rugby coaches to ensure the ecological validity, it deliberately sampled specific game scenarios in order to investigate the effects of controlled constraints. In particular, a full 15-a-side game would constitute a much more complex task, in which players continuously adapt to a richer and more dynamic landscape of affordances. It should also be considered that social identity processes may operate differently in other environments; for instance, the present findings may not fully reflect how such mechanisms function

in real-game contexts with more pronounced psycho-social stakes. Finally, future studies could investigate similar experiments across different populations, considering variations in age, gender, or competitive level, as these factors may also influence the role of social identity processes in players' interactions.

From a theoretical standpoint, this work therefore constitutes an experimental application for the combination of ecological psychology principles and social identity theory to understand interpersonal coordination processes. The concept of collective affordances (Weichold & Thonhauser, 2020) offers an interesting bridge between these frameworks, linking activation of social identity with the perception of action possibilities that are relevant for the team as a whole. However, this model appears to challenge the theory of shared affordances (Silva et al., 2013) which emphasizes coordination through affordances for and of others, that is, through couplings between teammates. In fact, the questions raised in Fajen et al. (2008) regarding the exact nature of the social affordances supporting interpersonal coordination remain open and continue to warrant empirical investigation: Do players need to be attuned to emerging affordances for the team? or Do players primarily coordinate by sharing affordances for others and/or of others? The present work does not allow for a direct examination of affordances themselves; rather, it captures the behavioral patterns that emerge from perception-action couplings, and more specifically their diversity. Future research should therefore aim to investigate more directly the ecological foundations of interpersonal coordination.

Furthermore, this work particularly underscores the importance of considering both the topology and spatial organization of player interactions to understand interpersonal coordination processes. Conceptually, this means that interpersonal coordination should not be reduced to who interacts with whom, but more accurately interpreted as the spatially embedded configuration of interaction patterns within which individual roles take shape. From this perspective, and in a more methodological perspective, the present study proposes a way to capture such configurations through social network analysis. Specifically, the concept of spatialized oriented graphlet (SOG) matrices allows integrating these two dimensions into a graphlet-based framework, as done previously in the flow motif framework (Barbosa et al., 2021, 2022). This methodological tool therefore supports player roles as emergent functional positions within structured interaction patterns, thereby offering a conceptual bridge between ecological dynamics principles and network-based models of interpersonal coordination.

However, another dimension of team sport phenomena is still overlooked: that is the dynamical interaction with the other team. While the relation with the opposing team was considered through the defenders' initial positions, the question of how this relation evolved throughout the trial was disregarded. Addressing this limitation would likely require extending the approach toward a dynamic analysis of SOG matrices over time, and moving beyond passing interactions to account for other forms of interpersonal couplings, such as relative motions or positionings. This would ensure a better fit with the evolving nature of a landscape of affordances that is shaped by others' actions (Passos et al., 2020). This remains a major challenge for fully capturing the real nature of sport teams through network approaches (Ramos et al., 2018; Buldú et al., 2018), which are complex adaptive systems dynamically interacting with a constantly changing environment. In addition, diversity – measured through entropy – was used as a central indicator because teams were conceptualized as complex adaptive systems exploiting degeneracy. However, differences in behavioral responses may not be reducible to variations in diversity alone (*i.e.*, more or less diverse team behaviors, more or less specialized player roles), and could also involve qualitative changes in coordination structures that were not fully captured within the present analytical framework.

## 5. Conclusion

By integrating concepts from ecological dynamics and social identity

theory, this study investigated how the interaction between a task constraint (defenders' initial positions) and an individual constraint (attackers' motivational goals) have participated in shaping interpersonal coordination in a rugby union small-sided game. The manipulation of defenders' positions clearly impacted attacking players' behavior, resulting in an adaptation of team coordination patterns and in the roles that players take within it, and this was moderately modulated by the priming of either self-oriented or team-oriented goals. This work also offers methodological advances for analyzing interpersonal coordination in team sports, notably through the development of spatialized oriented graphlet (SOG) matrices as a way to introduce both the spatial dimension and topological role of players within team coordination patterns.

**CRedit authorship contribution statement**

**Quentin Bourgeois:** Writing – original draft, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Guillaume**

**Hacques:** Writing – review & editing, Methodology, Formal analysis, Data curation. **Pedro Passos:** Writing – review & editing, Formal analysis. **Mickaël Campo:** Writing – review & editing, Project administration, Funding acquisition, Conceptualization. **Ludovic Seifert:** Writing – original draft, Supervision, Project administration, Methodology, Investigation, Funding acquisition, Conceptualization.

**IRB approval**

CERSTAPS [IRB00012476-2022-20-01-147].

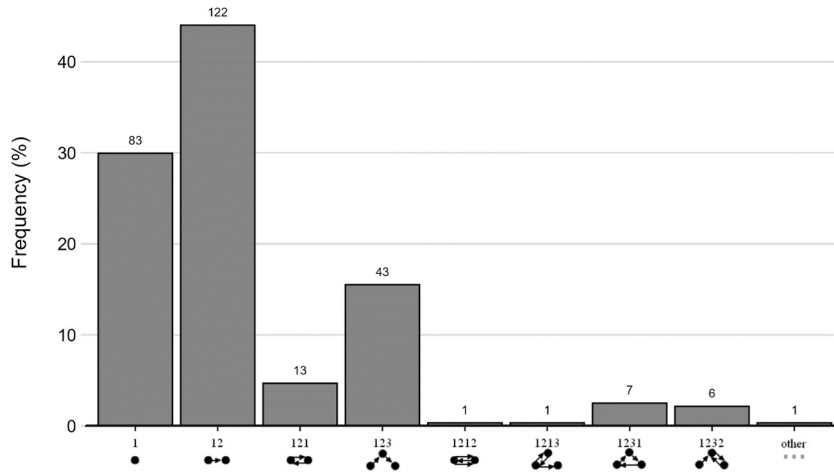
**Funding**

French ANR, ANR-19-STHP-0006 (TEAM SPORTS).

**Declaration of competing interest**

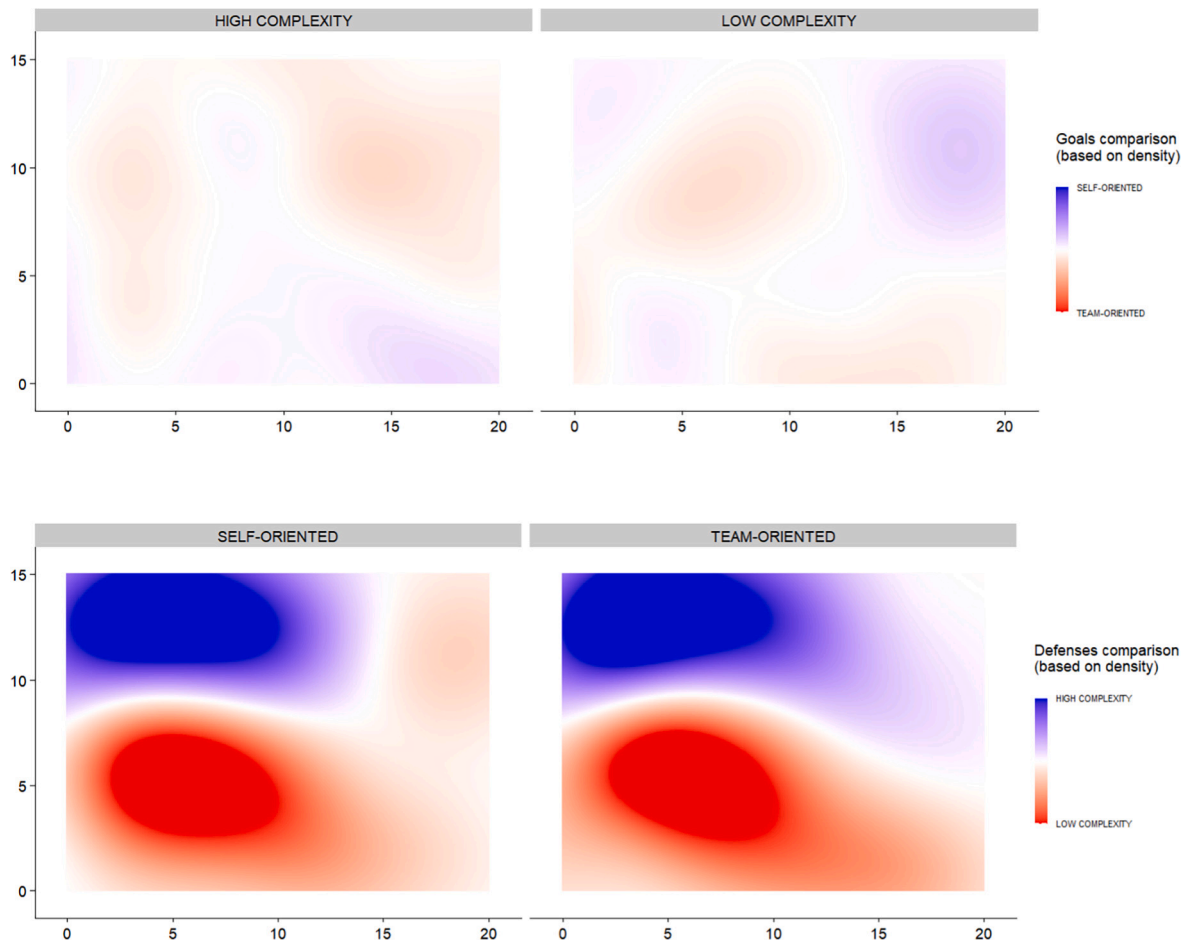
The authors have no potential conflict of interest to declare.

**Appendix 1. Unsuccessful trials**



*Graphlet frequencies for unsuccessful trials removed from the analyses*

**Appendix 2. Ball trajectories**

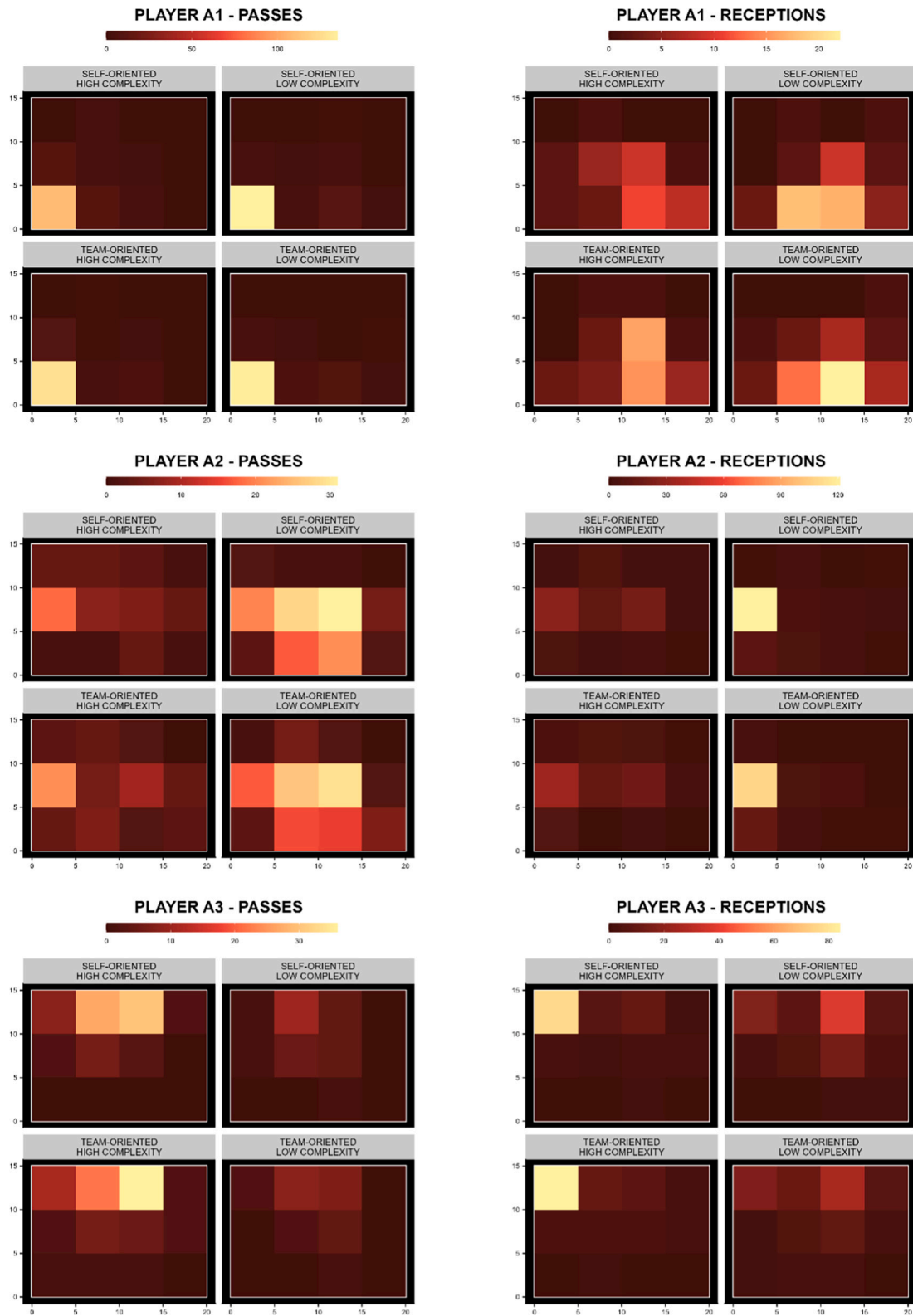


*Trajectories comparison based on density*

Note. The values represent the difference between two bivariate kernel density estimates computed on 2D positional data (X, Y) using a Gaussian kernel ( $h = 10$ ; using a  $250 \times 250$  grid, with  $X \in [0,20]$  and  $Y \in [0, 15]$ ). Colored areas indicate the presence of spatial differences in ball location between the two conditions (red or blue according to the direction of the difference), while white regions reflect areas with little or no difference in spatial distribution. A common color scale was applied to all plots (range:  $-0.002$ — $0.002$ ) to allow direct visual comparison of effect magnitude across panels.

**Appendix 3. Event–player matrices**

*Visualization of the event–player matrices*



Values of EMD contrasts and their respective 95% confidence intervals

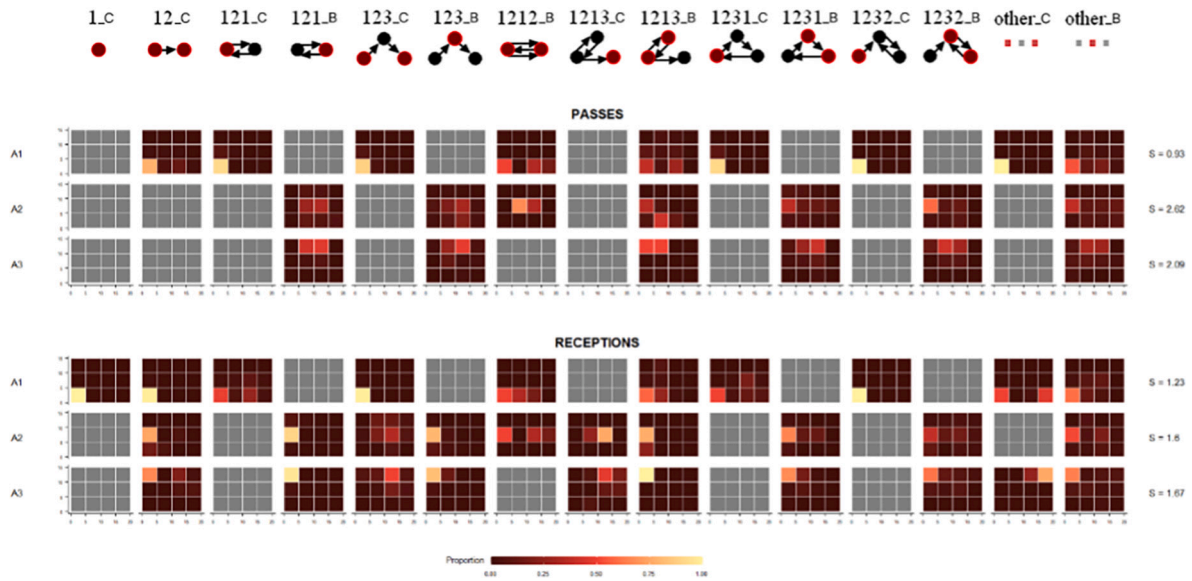
Comparison	Player	Event	EMD	Lower 95% CI	Upper 95% CI
DEFENSE COMPARISON for self-oriented goals	A1	Passes	0.75	0.58	0.90
		Receptions	2.04	1.70	2.45

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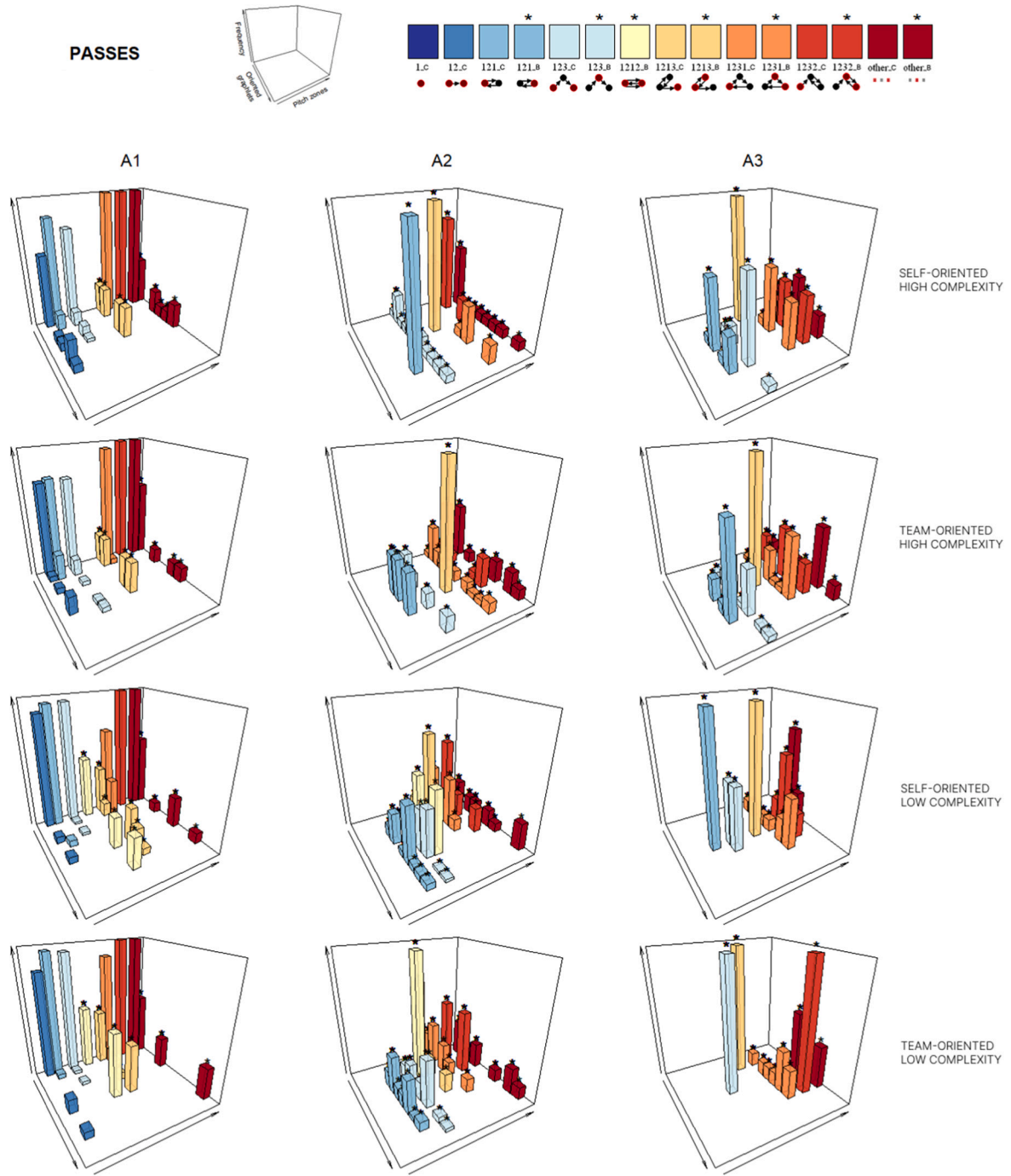
(continued)

Comparison	Player	Event	EMD	Lower 95% CI	Upper 95% CI
DEFENSE COMPARISON for team-oriented goals	A2	Passes	2.94	2.57	3.41
		Receptions	4.04	3.70	4.44
	A3	Passes	2.06	1.73	2.48
		Receptions	6.05	5.62	6.48
	A1	Passes	0.38	0.26	0.55
		Receptions	1.61	1.41	2.04
GOAL COMPARISON for high complexity situation	A2	Passes	2.52	2.17	2.95
		Receptions	3.94	3.54	4.28
	A3	Passes	1.35	1.08	1.80
		Receptions	5.58	5.17	6.07
	A1	Passes	0.55	0.40	0.74
		Receptions	1.19	0.94	1.64
GOAL COMPARISON for low complexity situation	A2	Passes	1.20	0.99	1.59
		Receptions	0.95	0.64	1.39
	A3	Passes	0.86	0.62	1.15
		Receptions	0.39	0.27	0.61
	A1	Passes	0.34	0.19	0.57
		Receptions	0.83	0.60	1.27
A2	Passes	0.53	0.43	0.81	
	Receptions	0.52	0.41	0.71	
A3	Passes	1.19	0.86	1.81	
	Receptions	0.83	0.65	1.27	

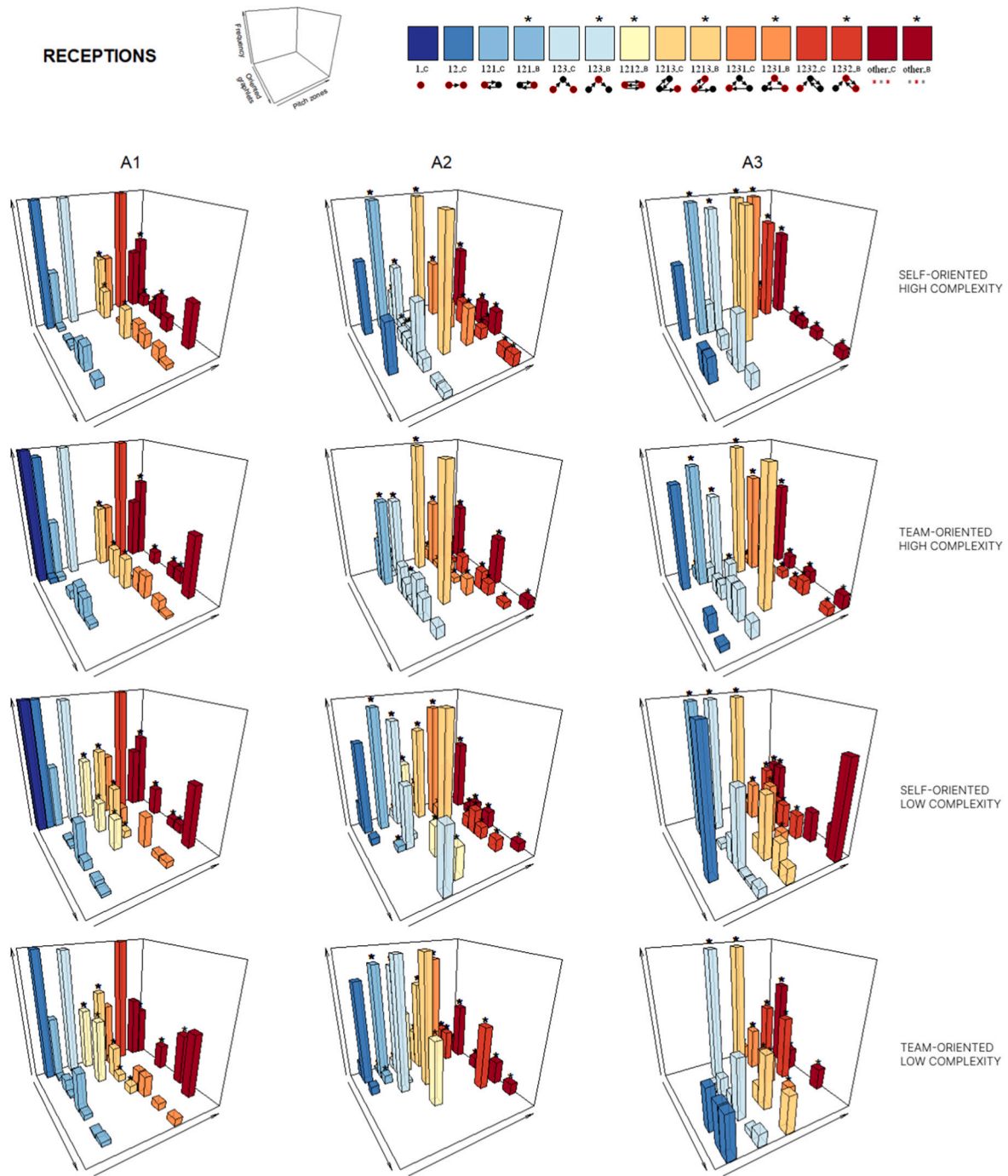
Appendix 4. Spatialized oriented graphlet matrices



Two-dimensional visualization of the spatialized oriented graphlet matrices.



Three-dimensional visualization of the spatialized oriented graphlet matrices, for passes.



Three-dimensional visualization of the spatialized oriented graphlet matrices, for receptions.

**Data availability**

Data will be made available on request.

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