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Using network science to unveil badminton performance patterns

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ABSTRACT

Bipartite networks are related to non-linear and ecological approaches where, at least, two different kinds of entities are considered. In sports, we can consider players as entities that base their decisions (actions and reactions) on opponents and their own actions. Incorporation of bipartite networks into modelling of racket sport performances may bridge the gap between the performance analysis sub-discipline and coaches for greater preparation of training sessions and competitions for enhanced success. Thus, the main aim of this study was to create badminton stroke networks (BSN), from the match activities of a player and their opponents, to describe and quantify the performance of elite Olympic badminton players. The use of a Network Science approach required the development of a series of methodologies that accounted for strokes played by all medallists within an Olympic tournament and included: (i) the construction of BSN; (ii) the one-mode projections of bipartite networks (self- and opponent- networks); (iii) the centrality of one-mode projections; and (iv) the identifiability of badminton players. The BSN identified different playing patterns for medallists with the Silver medallist categorised with the less predictable and defined style of play, the Bronze medallist exhibiting the most defined style; and the Gold medallist exhibiting the greatest predictability, but only when losing points (self-networks). The use of Network Science enabled the identification of distinctive styles of play (self- and opponent–related), based on stroke performance, during successful and unsuccessful points within an Olympic tournament. Specifically, the identifiability of each player's network and its associations with point outcome, provided a better understanding of stroke performances and individual features of world-class badminton players. The use of non-linear approaches (such as bipartite networks) to measure and visualize player's performances, accounting for the specific nature of badminton and opponents, may support coaches and players with the contextualized demands of playing patterns and their performances (i.e., winning and losing points) for future success.

1. Introduction

Performance analysis studies of racket sports such as squash [1–4], paddle [5,6], tennis [7–9] and table tennis [10–12] have focused on the importance of players' spacing and tactics to define patterns for players' match-related performance. In contrast, notational analysis of badminton performance has examined key performance indicators (KPI, e.g. distribution of strokes, zones of the court used, frequency of technical actions and their effectiveness) to identify player's patterns during competition [13] as well as identify differences between sexes [14–16], elite and sub-elite players [17] and competition stages [18,19]. These analyses highlighted vital player actions and strategies for success (e.g. hitting the shuttlecock to the least favorable area for the opponent). Success in badminton is achieved by forcing the opponent to perform strokes under spatial pressure, with shots located to the corners of the court, or close to the net, generating future open spaces and gaps to play the shuttlecock towards [20,21]. Despite this general tactical pattern, each player's individual features (i.e., handedness, height, physical fitness, etc.) may also modify their behavior and playing patterns to counteract a specific opponent [22–24]. Understanding the temporal, technical, tactical and movement contributors to how each individual plays may improve identification and recognition of "performance profiles" [25] and a clear visual interpretation of strengthens and weaknesses for sport science (e.g. analysts) and practice (e.g. coaches and players).

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One of the most intriguing analyses in badminton has been modelling the evolution of positional information about players and the strokes performed. In fact, the visualization of performance patterns has been reported to generate a better interpretation of opponent-related contexts for success [13]. Only a few studies have examined match-related performances from a video-analysis perspective, focusing attention on the extraction of shuttlecock trajectories, and classifying the serve and strokes used during matches [26]. Recently, Chu and Situmeang [13] employed video analysis to document badminton player's strategies according to space, opponent strength, and type of stroke (i.e., technical actions) with performance models generated based on classification and detection statistics. Despite this initial approach to analyze player's performance patterns/profiles, consideration of opponent-related actions based on space and success has yet to be incorporated for badminton [15,24].

Badminton is a unique sport that differs from other racket sports (i.e., tennis or paddle) due to the rapid responses required during high-intensity actions involving a shuttlecock flying at high speeds that does not make contact with the ground (i.e., similar to volleyball). Consequently, performance analysis and interpretations must consider multivariate, contextual-related and non-linear methods relevant to the opponent's performances [27]. The use of isolated variables (e.g., technical-tactical indicators) without contextual interpretation of player's positioning during performances may provide misleading information. According to Hughes et al. [25] racket sports, such as badminton, require the inter-related analysis of pace, space, playing actions and players' modified attacking/defending actions in response to their opponent's constraints.

From a statistical point of view, linear approaches have been used predominantly in prior racket sport studies [25] however, these simplistic models neither adequately quantify nonlinear behaviors between badminton counterparts, nor provide a visualization tool for coaches and players [25,28]. Indeed, the use of non-linear approaches within sport science analyses would offer an improved approach to address complex sport performance research questions (e.g. interdependence of counterparts' performances according to space and success) while providing valuable data visualization regarding each specific match-context (i.e. player's characteristics) [29–31]. Perl [30] highlighted the utility of non-linear models, such as neural networks and fuzzy logic, to predict player's performance with consideration of match-related factors (e.g., accumulated fatigue and environment conditions: temperature or fan support) in racket sports. For example, Perl and Baca [29] used neural networks (Kohonen Feature Maps, KFM) that considered the time-series actions performed during rallies to identify performance patterns of table tennis players based on space and frequency. However, this model only accounted for the time-dependent aspects of performance without consideration of the relationships with opponent's performance, success or context (set or match). Therefore, understanding the effect of oppositional play is essential to define and predict typical performances (tactical nature) for match effectiveness [25,32,33]. The use of complex and non-linear analyses, such as Network Science [34], may provide a unique approach to model performances from an ecological, multivariate and context-related perspective.

Different methodologies grounded in Network Science have been used to analyse a variety of sporting contexts including the structure of the transfer market in football [35] (Li et al., 2019), the success probability of a rugby team [36] and development of an all-time ranking of national football teams based on their scores during world championships [37]. Importantly, Network Science has been proposed to quantify and resolve the particular playing patterns of teams [38] or players [39]. For example, using spatio-temporal coordinates of all passes made during a football match, it was possible to construct the passing network of both teams and analyze its topology related to the team's performance [40,41]. Furthermore, certain network parameters, such as the flow centrality [42], the eigenvector centrality [39] or the participation of a player in the construction of network motifs [43], have been associated with identification of playing patterns' similarities/differences between specific football players. The use of Network Science to characterize playing patterns appears to be an important and emerging approach for sport analyses including that of badminton players [35–42].

In particular, bipartite networks can be related to non-linear and ecological approaches that consider players as organisms who base their decisions (actions and reactions) on opponents and their own actions [44]. Previous studies have examined football and rugby teams using this ecological approach and considered them as superorganisms [45,46]. The use of bipartite networks may bridge the gap between the performance analysis sub-discipline and coaches modelling performances and predicting player's patterns [25]. Therefore, our ultimate purpose was to construct *badminton stroke networks (BSN)*, from the match activities of a player and his/her opponents, to describe and quantify the performance of elite badminton players. Using a Network Science approach, a series of methodologies (i) the construction of BSN; (ii) the one-mode projections of bipartite networks (self- and opponent- networks); (iii) the centrality of one-mode projections; and (iv) the identifiability of badminton players) could be developed to assist elite badminton coaches and athletes in the preparation of training sessions and competitions for enhanced success.

2. Methodology

2.1. Dataset

The dataset examined included all rallies (N_r=1052) and strokes (N_s=11,158) of 14 matches played by the three female medallists during the singles competition of the 2016 Olympic Games (Rio de Janeiro, Brazil). Each player played up to 6 matches with all match data examined in the current study, except for the bronze medal match where the medallist incurred an injury and performed sub-optimally. Subsequently, each player contributed data from 5–6 elite matches, in accordance with the recommended number of matches (3–7) to establish normative profiles of performance [21]. Strokes made during a match were sequentially ordered with the following information obtained per stroke: (i) set, (ii) point, (iii) stroke number in the point, (iv) player who made the stroke, (v) zone from where the stroke was made (12 zones each player's court, see Fig. 1A), (vi) X-axis coordinate of the stroke, (vii) Y-axis coordinate of the stroke and (viii) the stroke's outcome (point win or lose). Table 1 shows an example of four consecutive strokes made during the 2016 Olympic final.

Table 1
Example of the collected information for each stroke. We identified the (i) set, (ii) point, (iii) stroke number in the point, (iv) player who made the stroke, (v) zone from where the stroke was made, (vi) X-axis coordinate of the stroke, (vii) Y-axis coordinate of the stroke and (viii) the stroke's outcome classified as one of 2 different results: (a) point won, and (b) point lost when the shuttlecock was out of the court or hit net.

Set	Point	Stroke	Player	Zone	x	y	Outcome
…	…	…	…	…	…	…	…
1	3	3	Player 1	8	−14	−35	Point won
1	3	4	Player 2	1	−15	14	Point won
1	3	5	Player 1	9	−13	55	Point won
1	3	6	Player 2	6	1	−24	Point lost
…	…	…	…	…	…	…	…

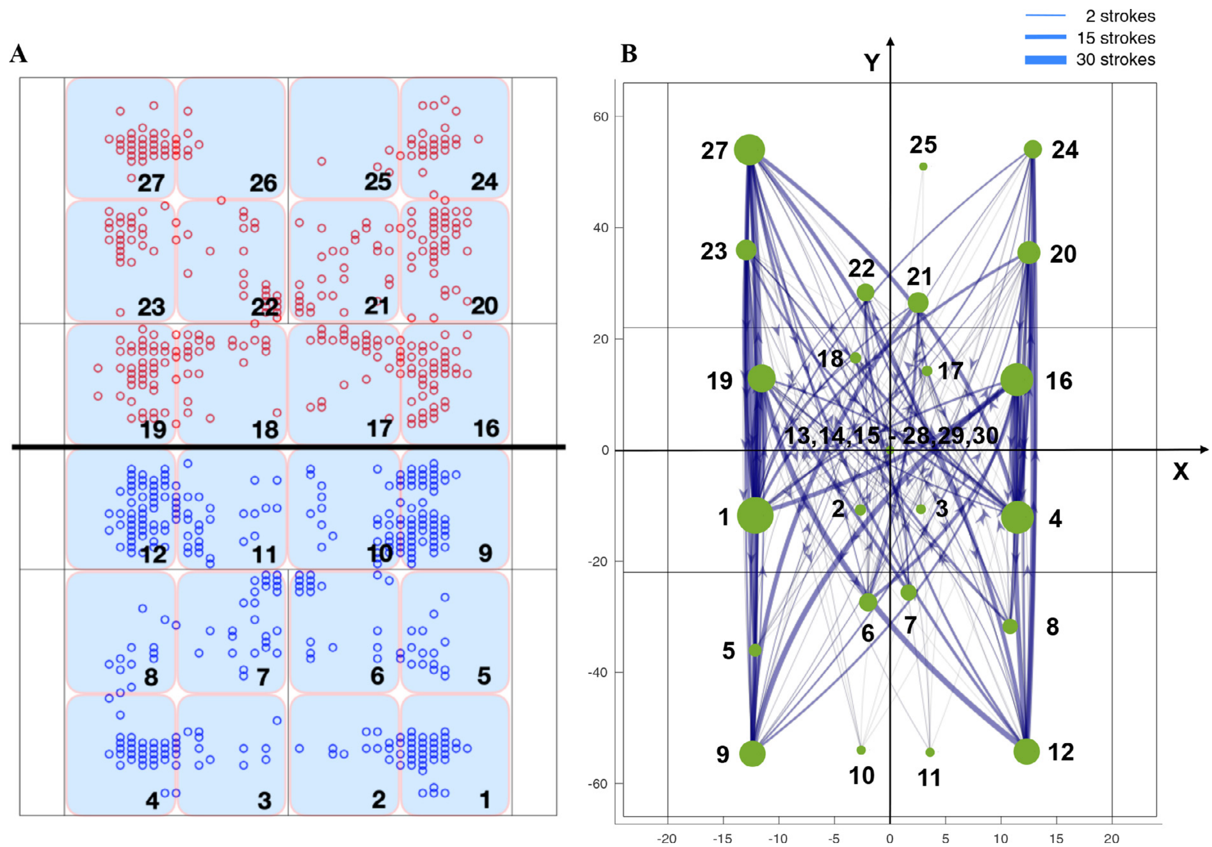

Fig. 1. A) Position of all strokes made during the final of the 2016 Olympic Games. All strokes made by the gold medallist (Player #1) were plotted at the bottom part of the court while all strokes made by the silver medallist (Player #2) were shown in the upper part. B) The corresponding badminton stroke network (BSN) for the final of the 2016 Olympic Games is displayed. For Player #1, nodes inside her part of the court were labelled from 1 to 12. Nodes 13, 14 and 15 corresponded to "out", "hit net" and "win", respectively. For Player #2, nodes were labelled from 16 to 27, while nodes 28, 29 and 30 were labelled "out", "hit net" and "win", respectively. The nodes located at coordinates 0,0 were disregarded during the network analysis. Size of nodes was proportional to the importance of that position in the network with the value corresponding with the eigenvector centrality [34]. The width of the links, which are unidirectional, was proportional to the number of times the shuttlecock went from one node to the other. Finally, the position of the nodes corresponded to the average number of all strokes belonging to each region.

All match recordings were obtained from matches publicly available on TV, imported into Dartfish (Friburgo, Switzerland) and analysed independently by four trained observers (Sports Science graduates with ten years of national experience as badminton coaches). The inter- and intra-rater reliability values between the four observers were very good for outcome (Kappa: >0.85). The spatial classification was automatically made by the software identifying the x/y measures for each zone of the court (there was enough resolution to include each stroke in one zone). Additionally, there was calculated the Weighted Kappa for spatial variables in order to check the data reliability for zones of the court with very good values (>0.81) [47,48].

Overall, a series of procedures were undertaken for this study as follows: (i) the construction of Badminton stroke networks (BSNs); (ii) the one-mode projections of bipartite networks (self- and opponent- networks); (iii) the centrality of one-mode projections; and (iv) the identifiability of badminton players.

2.2. From strokes to badminton stroke networks (BSN)

Badminton stroke networks (BSN), whose fundamental nodes are the regions of the badminton court where a player makes a stroke and the links arising from the trajectories of the shuttlecock between two areas of the court, which are located on different sides of the net, were developed. Fig. 1A shows the position of all strokes that occurred during the Olympic final. Strokes made by Player #1 (the winner and gold medallist) have been placed at the bottom part of the court, while those of Player #2 (the silver medallist) are in the upper part.

Next, we obtained the corresponding BSN of the match (Fig. 1B). To do so, the first step was to define the nodes of the network, which corresponded to the different areas of the court. In our case, we divided each side of the court into 12 regions (Fig. 1A). Nodes placed at the bottom part of the court were labelled n_i=1,2,..,12 and contained the strokes of Player #1. We also included 3 nodes that did not correspond to any area of the court (nodes 13, 14, 15; located at coordinates 0,0) but were related to the outcome of each point such as “out”, “hit net” and “win”, respectively. In the same way, nodes of the upper part of the court were labelled n_i=16,17,..,27 and corresponded to nodes of Player #2. All nodes located at coordinates 0,0 were disregarded from the network analysis since we were concerned about the movement of the shuttlecock during the game. Therefore, our initial analysis was based upon a network of $N = 24$ nodes. Links between the nodes and their corresponding weight were then determined. Unidirectional links connected two nodes (areas) when the shuttlecock flew from one region of the court to a region on the other side of the net. The weight w_{jk} of a link connecting node j to node k represented the number of times the shuttlecock was hit from region j to region k. It is worth noting that the position of the nodes was not exactly the same on both sides of the court as we placed each node at the average position of all strokes contained in the area assigned to that specific node. As a consequence, it was possible that a node was missing, which occurred when no successful strokes were made from that specific region (e.g., node #26). In order to include as much information as possible in the representation of the BSN, node sizes were proportional to the eigenvector centrality of each node [34], which was a measure of the importance of the node in the global structure of the stroke network.

2.3. Constructing the one-mode projections of BSN

Note that BSN are a paradigmatic example of bipartite networks where nodes are grouped into two disjoint sets, with nodes of the same set devoid of a direct link between them [34]. For BSN, each disjointed set of nodes corresponded to the nodes located on the same side of the court with links only connecting nodes located on different sides.

When analysing bipartite networks, it is possible to project the information into two, different one-mode projections [38,49], containing the activity of what is happening on each side of the court. In one-mode projections, links between nodes of the same kind are created, which in our case was the same side of the court. With this aim, an area j was connected to another area k on the same side if the shuttlecock departed from area j, went to an area i on the other side of the net and, then went back from area i to k. Note that, in addition to the path the shuttlecock moved, we captured the routes followed by a given player when they hit the shuttlecock from regions j to i and then received it back to region k to make the next stroke. Fig. 2 shows the one-mode projections (one per player) of the BSN plot in Fig. 1B and included the order of displacements during the match. The number of nodes was $N_1=N_2=12$ for each one-mode projection with the projection corresponding to Player #1 shown in the bottom part while the upper part represented the projection for Player #2 (Fig. 2). The size of the nodes was proportional to their importance in the one-mode projection network with the width of the links proportional to the number of times a specific path was repeated.

We focused on the properties of unique one-mode projections that were developed for each player and represented their playing pattern against a specific opponent. In order to characterize the structural properties of the one-mode projections, we computed the following network parameters:

2.3.1. Clustering coefficient (C)

In general, the local clustering coefficient of a node i was obtained as the percentage of the nodes directly connected to i that, in turn, were connected between themselves [34]. This measure was averaged over the N nodes of a network to obtain the average clustering coefficient, C. However, when the network is weighted and directed, then the distribution of these weights and directions should be included in the calculation of the clustering coefficient. This was the case for BSN, where the number of connections between the areas of the court was not constant. Therefore, we use the weighted clustering coefficient $C_w(i)$ to measure the likelihood that neighbours of a given area i were also connected between themselves [50] as follows:

$$C_w(i) = \frac{\sum_{j,k} w_{ij} w_{jk} w_{ik}}{\sum_{j,k} w_{ij} w_{ik}}$$

where j and k are any two areas of the court and w_{ij} and w_{ik} are the number of times the shuttlecock flew between area i and both area j and k. Finally, the clustering coefficient of the network was obtained as follows:

$$C = \frac{1}{N} \sum_{i=1}^{N} C_w(i)$$

In short, the weighted version of the clustering coefficient characterized the tendency of a badminton player moving within triangular patterns between areas of the court.

2.3.2. Shortest-path length (d)

In a BSN, the shortest path length d is the minimum number of areas that must be traversed by the shuttlecock to go from one area to any other. Since BSN networks are weighted networks, we must take into account the different weights of the links, considering that, the higher the weight of the link connecting two nodes, the shorter the topological distance between them. Therefore, the topological length l_{ij} of the direct link between areas i and j is defined as the inverse of the link weight, $l_{ij} = 1/w_{ij}$. Importantly, when computing the shortest-path length between two nodes in weighted networks, it may not be a direct link between them as a shorter path could exist by combining two (or more) alternative links whose topological lengths summed are lower than the length of the direct path. Therefore, we computed the minimal shortest-path p_{ij} between any node i and j using Dijkstra's algorithm [51], which obtained the path (or combination of paths) between all pairs of nodes, for the lowest topological distance. We defined the average shortest path d of the whole network as:

$$d = \frac{1}{N(N-1)} \sum_{i,j\ i \neq j} p_{ij}$$

where $N = 24$ for BSN and $N = 12$ for each of the one-mode projections.

2.3.3. Largest eigenvalue (λ_1)

The largest eigenvalue λ_1 of the weighted adjacency matrix $\boldsymbol{A}$ of a network is a measure of the network strength [34]. The weighted adjacency matrix $\boldsymbol{A}$ is a $\boldsymbol{N} \times \boldsymbol{N}$ matrix whose elements $\{a_{ij}\}$ contain the weight of the links connecting area i with area j. The largest eigenvalue of $\boldsymbol{A}$ was bounded by the average weight of the network $<w_{ij}>$ and the maximum number of times the shuttlecock connected any two areas w_{max}, with $w_{max} \geq \lambda_1 \geq \max\{<w_{ij}>, \sqrt{w_{max}},\}$ [52]. As a rule of thumb, networks with higher weights would have a higher λ_1 while networks with strong connections between nodes (known as assortative networks) would also have higher λ_1 compared with networks where the hubs (i.e., areas with the highest weights) were not directly connected.

2.3.4. Eigenvector centrality [ec(i)]

The eigenvector centrality $ec(i)$ of an area i is a measure of node importance that takes into account the number of all directed connections within an area. It is calculated from the eigenvector $\boldsymbol{v_1}$ associated to the largest eigenvalue λ_1 of the weighted adjacency matrix $\boldsymbol{A}$ [34]. Furthermore, two factors contribute to a greater eigenvector centrality: (i) a greater number of direct connections to different areas of the court (note that connections are weighted); and (ii) a greater number of connections to areas that, in turn, also have a high centrality. In other words, important nodes are those areas of the court that are (highly) connected to other important areas of the court. Eigenvector centrality is one of the most important metrics to evaluate the importance of a node in a network [34] with a modified version, the PageRank algorithm, utilised by Google to quantify the importance of webpages [53].

2.3.5. Network randomization and normalized parameters

In order to interpret the values of the network parameters, we constructed the randomized versions of the original networks and calculated their corresponding network parameters. First, we randomized the weights of the links of a BSN, reshuffling (randomly) the elements of the adjacency matrix $\boldsymbol{A}$. The randomized version of the adjacency matrix $\boldsymbol{A}$ was termed $\boldsymbol{A}_{ran}$. Second, we calculated all network parameters for the randomized versions of matrix $\boldsymbol{A}$. Next, we repeated the process 100 times and obtained an average value $<X_{ran}>$ of each parameter X_{ran} of the randomized networks. Finally, we obtained the normalized parameters of the original networks,

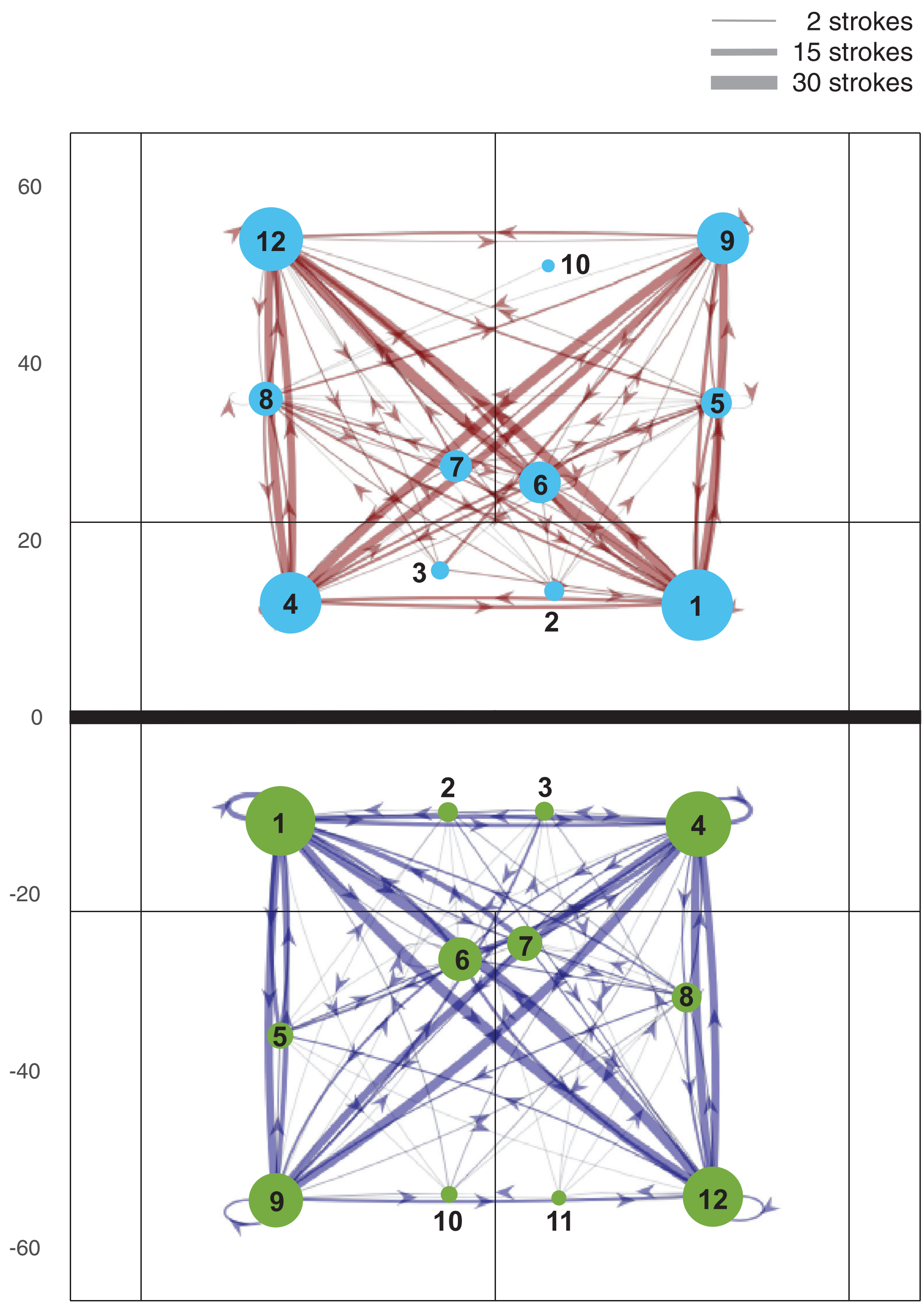

Fig. 2. Example of the one-mode projections of a BSN during the final of the 2016 Olympic games. The projection of the gold medallist (Player #1) was displayed in the bottom part of the court while that of the silver medallist (Player #2) was shown in the upper part. One-mode projections of each player's displacements were obtained by connecting nodes *j*-*k* on the same side of the court, when the shuttlecock left position *j* and returned to position *k* (after the stroke of the opposite player). The width of the links represented the number of times a specific path was repeated. As in Fig. 1, the size of the nodes was proportional to the importance of that position in the one-mode projection and was obtained from the calculation of the eigenvector centrality. Finally, the position of each node corresponded with the average number of all strokes belonging to each region.

dividing the original parameter X by $<X_{ran}>$ (e.g. the normalized clustering coefficient was obtained as $C_{norm}=C/<C_{ran}>$). Note that normalized parameters have two advantages: first, they allowed us to determine if a network was close to a random one (which would be the case when values of X_{norm} were close to one); and second, they allowed comparison between the parameters of networks with different number of nodes and links.

2.3.6. Small-worldness parameter (SW)

The small-worldness parameter was calculated from the combination of two network parameters: the normalized clustering coefficient and the normalized shortest-path length [54]. Specifically, it was defined as $SW= (C/<C_{ran}>)/(d/<d_{ran}>)$. Values of SW greater than one indicated that a network was small-world, while values close to one suggested that the network may be random. The SW parameter has been computed in a diverse range of social, biological and technological networks with values greater than one reported for the majority of networks [55,56].

2.3.7. Centrality of one-mode projections

The centrality (i.e., importance) of each node during the match and how it was related to winning or losing a point was calculated for each player/opponent. Specifically, we first obtained the winning and losing BSN, and then computed the corresponding one-mode projections. Next, we calculated the eigenvector centrality of all areas of the court for each winning/losing network ($ec_{win}(i)$ and $ec_{lost}(i)$, respectively). Finally, for each area, we subtracted the centrality obtained for the losing network from the one obtained for the winning network, leading to the centrality difference $\Delta ec(i) = ec_{win}(i) - ec_{lost}(i)$. Positive values of $\Delta ec(i)$ for a given area i indicated that this area contributed importantly in winning the point, compared to when the point was lost. On the contrary, negative values of Δec highlighted areas that were important for losing a point. This analysis provided a novel perspective that could help (i) detect weak and strong areas of the court for players; and (ii) prepare for a badminton match against specific rivals (by analyzing their corresponding networks).

2.3.8. Identifiability of badminton players

Finally, we examined whether the playing style of a player could be identified by the structure of their corresponding BSN. With this focus, we computed the identifiability of the networks [57,58] by evaluating the correlation between the adjacency matrices $\boldsymbol{A}$ of the one-mode projections of a given player, and then comparing it with the correlations between the networks of other players. As explained in the previous section, each BSN can be decomposed into two one-mode projections, one per each player of the match. Therefore, we first obtained the adjacency matrices of the one-mode projections of a player $\{\boldsymbol{A_{self}(k)}\}$ and their opponent $\{\boldsymbol{A_{opp}(k)}\}$ for the k matches played by each player. Next, we computed the correlation coefficients between all $\{\boldsymbol{A_{self}(k)}\}_j$ of a given player j and obtained the *self-identifiability* $I_{self}(j)$ of player j as the average of the $k(k-1)/2$ possible combinations. This parameter indicated how similar the matrices of a player were with values of $I_{self}(j)$ close to one indicating a greater, playing style similarity. Next, we calculated the *opponent-identifiability* $I_{opp}(j,r)$ of a player j with an opponent r as the average correlation between matrices $A_{self}(j)$ (of player j) and matrices of $A_{self}(r)$ (of player k). As stated earlier, values of $I_{opp}(j,r)$ close to unity indicated a similar playing style between player j and their opponent player r.

Note that the ideal performance combination for a player was a high value of $I_{self}(j)$ and a low value of $I_{opp}(j,r)$. Finally, a player's identifiability $I(j)$ was calculated as:

$$I(j) = I_{self}(j) - \langle I_{opp}(j,r) \rangle$$

Finally, we carried out a series of analyses dividing the self-networks according to the outcome of the point in order to relate the playing pattern with the performance during the point (win or lost). For example, we considered only those strokes that resulted in winning the point, and defined the self-win-networks accordingly. Likewise, we obtained the self-lost-networks considering strokes that resulted in losing the point.

3. Results

3.1. Network parameters

The average values for the $\lambda_{1,norm}$, the C_{norm}, the d_{norm} and the SW metrics (during the tournament) for each player are shown in Fig. 3.

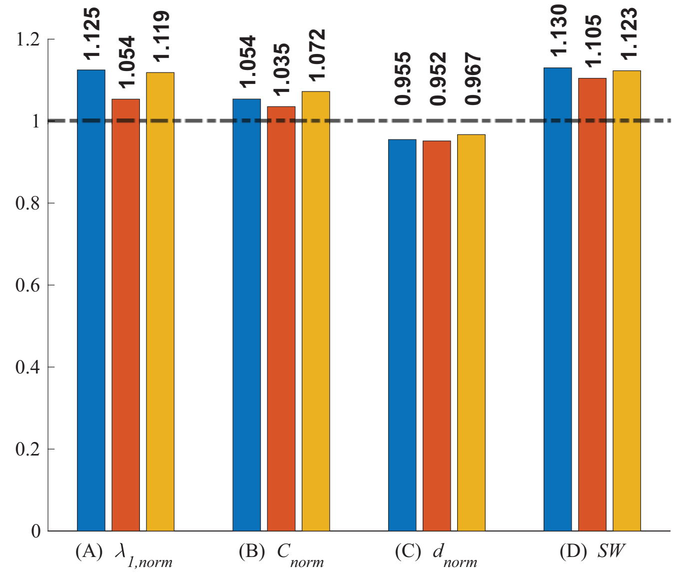

Fig. 3. Network metrics of the three Olympic medallists: Gold medal (blue), Silver medal (red) and Bronze medal (orange). (A) the largest eigenvalue of the one-mode projection adjacency matrix $\lambda_{1,norm}$, which was normalized by the value of the corresponding random ensemble; (B) the normalized clustering coefficient C_{norm}; (C) the normalized shortest path d_{norm} and (D) the small-worldness parameter SW.

Interestingly, the $\lambda_{1,norm}$ of the three medallists was consistently greater than one indicating that (i) the one-mode projection network of each player was not purely random and (ii) the areas of the networks with greater numbers of connections were, in turn, highly connected. Concerning the C_{norm}, all players exhibited a value that was greater than unity, indicating that triangular movements within the court were prominent (Fig. 3).

The normalized shortest-path length d_{norm} was, contrary to the previous metrics, lower than unity (i.e. random networks) and indicated that the distance (i.e., areas to traverse) covered by players was lower than that covered randomly (Fig. 3).

Finally, the SW was overall greater than one (Fig. 3) for all players, which highlighted that one-mode projections of BSN digressed from being random and, in turn, players' court displacement patterns exhibited better organizational properties than their equivalent random networks.

3.2. Centrality of one-mode projections

Based upon the one-mode projections of the networks and point outcome (Fig. 4), positive values of $\Delta ec(i)$ at a given area i green circles of Fig. 4 identified important areas for winning points while negative values of Δec red circles of Fig. 4 highlighted areas that were important when losing the point. Results shown in Fig. 4 correspond to the average values during the tournament obtained for the three medallists.

3.3. Identifiability of badminton players

Positive identifiability $I(j)$ of all three medallists is shown in Fig. 5. Interestingly, the bronze medallist exhibited the most defined style while the silver medallist was the one with the least defined style. In turn, Fig. 5B shows the identifiability parameters obtained at the opponents' networks. Interestingly, values were slightly lower for opponent's networks compared to those obtained for self-networks. However, when obtaining the identifiability $I(j)$ of each player, we observed some higher values than those of the self-networks (see Fig. 5C and D).

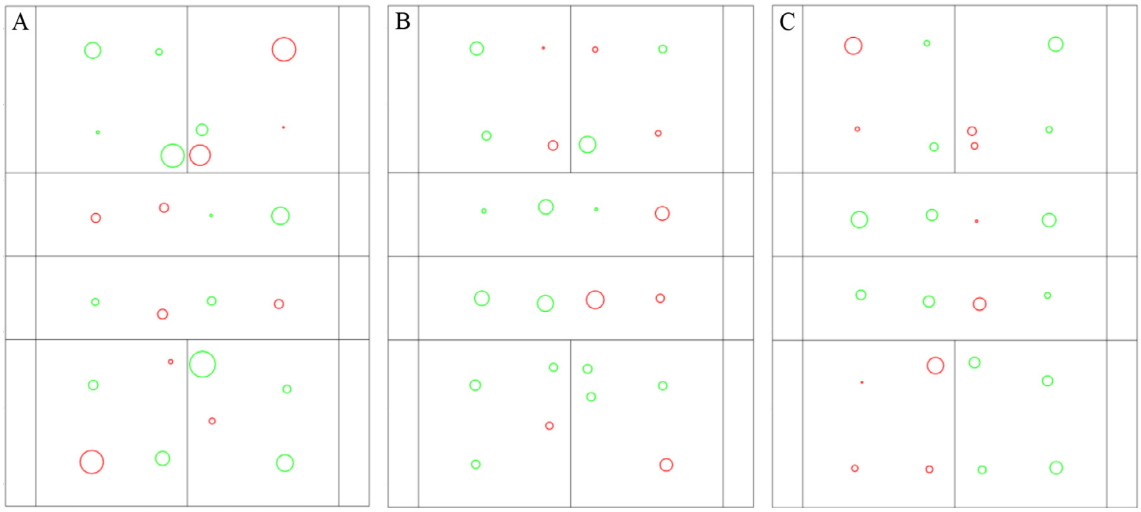

Fig. 4. Relevance of player position according to point result during the final of the 2016 Olympic Games with the gold (A), silver (B) and bronze (C) medallists. $\Delta ec(i)$ is the average (during the tournament) of the difference between the importance (i.e., eigenvector centrality) $ec_{win}(i)$ of each area when a point was won, minus the importance $ec_{lost}(i)$ of the same area in the network obtained when the point was lost. Green circles indicate those areas with higher centrality during winning points, while red circles correspond to areas that were more important during points that were lost. Size of the circle is proportional to the magnitude of the differences between centralities $\Delta ec(i)$. *Average values of the medallists are plot at the bottom part of the court, while the averages of their opponents during the tournament are plot in the upper part.*

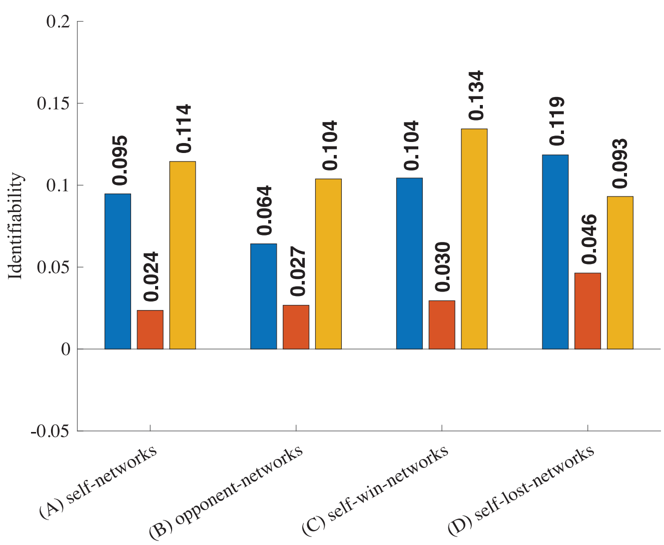

Fig. 5. Identifiability of different one-mode projection networks of the three Olympic medallists (Gold medal: blue, Silver medal: red and Bronze medal: orange): (A) self-networks of each player, (B) self-networks of the opponent for each match, (C) self-networks during points won, (D) self-networks during points lost.

Finally, Table 2 showed the style of playing for each player with high values of the diagonal correlation corresponding to the $I_{self}(j)$ and low, off-diagonal correlation values $I_{opp}(j,r)$ noted for the three medallists (Table 2). Irrespective of the point result (winning or losing point), the absolute correlation values for all strokes of the self-network were greater (Table 2).

4. Discussion

The aim of the current study was to construct networks from the match activities of badminton players in order to describe and quantify their performance. The development of *BSN* based on the areas of the badminton court used by players during points (trajectories of the shuttlecock between two areas of the court) identified different and unique measures of player's performances: (i) one-mode projections of bipartite networks (self- and opponent-networks); (ii) the centrality of one-mode projections; and (iii) the identifiability of badminton players. These measures identified different playing styles for medallists with the silver medallist exhibiting the least predictable and defined style of play, the bronze medallist exhibiting the most defined style, and the gold medallist exhibiting greater predictability, only when losing points (self-networks). Further, Network Science methodologies were able to clearly describe and quantify the point performance of elite badminton players including self and opponent related networks, and their association to winning and losing points. Specifically, the BSN models indicated the need to account for individual features (playing patterns) with coaches and performance analysts encouraged to be aware of the opponent's style of play [59].

The utility of novel analytical approaches are of great interest for coaches and players with the current one-mode projections providing clear profiles for a given player and their rival. In particular, these analyses identified the idiosyncratic, playing style of medallists from positional, stroke and outcome related perspectives. Further, the current approach of using bipartite networks unveiled tactical performance patterns of each player and improved the utility of this model when assessing performance trends during different contexts and tournaments [60]. The use of bipartite networks was in accordance with non-linear and ecological approaches, where athletes are considered as organisms that base their decisions (movements and behaviors) on opponents and their own actions [44]. Similar approaches have been widely developed in team sports (such as football or rugby) under the ecological approach (i.e., considering teams as superorganisms) with concluding implications and applications to training design and competition management established [45,46]. Collectively, these complex approaches and analyses have assisted in bridging the gap between sports sciences (performance analysis sub-discipline) and coaching to predict future player's patterns/ performances in subsequent matches (contexts) accounting for opponents' features/ characteristics [25].

The current results confirm prior work that individuals' performances were affected by the opponent who is the core of the network model and a major source of player's performance variability [33,61]. Therefore, the recognition of strengths and weaknesses relevant to opponents will allow players to maximize their performances, exploit the opponent's weaknesses (e.g., use of zones,

Table 2
Correlations between players' self-networks, opponents' networks, and players self-network during winning and losing points, for each of the three medallists. Note that values in the diagonal (in bold), indicating the average correlation of each player with themselves, were always greater than correlations between each player and the other two (off-diagonal values).

Player	Gold medallist	Silver medallist	Bronze medallist
Player's self-network			
Gold medallist	**0.780**	0.676	0.694
Silver medallist	0.694	**0.697**	0.667
Bronze medallist	0.669	0.670	**0.797**
Player's opponents-network			
Gold medallist	**0.766**	0.701	0.702
Silver medallist	0.701	**0.720**	0.686
Bronze medallist	0.702	0.686	**0.798**
Player's self-network during winning points			
Gold medallist	**0.726**	0.610	0.633
Silver medallist	0.610	**0.637**	0.605
Bronze medallist	0.633	0.605	**0.753**
Player's self-network during losing points			
Gold medallist	**0.673**	0.537	0.572
Silver medallist	0.537	**0.578**	0.640
Bronze medallist	0.572	0.640	**0.642**

strokes and point pace based on those tactical patterns that ended with a point won) and avoid situations where the opponent is strong. As demonstrated in the current study, the bipartite networks allowed establishment of performance pattern analyses as follows:

(i) The strokes to badminton networks produced a visual tactical pattern that was based upon match context (opponent-related) and could be used by players when preparing matches against specific opponents (i.e. playing pattern trends);
(ii) The use of one-mode projections of a bipartite strokes network revealed the importance of each player's individual features. For example, Fig. 2 showed those paths that had been crossed the most (by means of the links' thickness) and those areas that had been most influential to the stroke network (indicated by the node size), both for a player and their rival.
(iii) Tactical patterns during matches including the positional dimension and strokes played during points were identified for both players with players' predictive performance improved when the following four network properties were examined collectively: $\lambda_{1,norm}$ eigenvalues and C_{norm} coefficients (controlling for randomness network and triangular movements along the court, respectively), the d_{norm} (the number of steps to go from one zone to another of the court during the point), and *SW* parameters (the ratio between the normalized clustering and normalized shortest path). This unique and comprehensive analysis confirmed that the silver medallist of the 2016 Olympic Games was the player with the greatest random playing patterns compared with the gold and bronze medallists (see Fig. 3).
(iv) Centrality of one-mode projection provided valuable information of player's effectiveness according to point outcome with the most important nodes identified for both players. For example, Fig. 4 displayed the areas of the court where a player was at a higher risk of losing a point. Such reconnaissance about opponents would assist players in preparation of match tactics when they competed.
(v) Identifiability of badminton players identified the style of play of a given player based on their own, and opponents, structure of one-mode projections of the stroke network. Therefore, identifiability enables a clear identification of the similarity of the playing styles of a player and their opponent In the current study, again, the silver medallist was acknowledged as the player whose style was the most difficult to be identified. On the contrary, the bronze medallist was the player with the most defined patterns and greatest identifiability.

We employed a non-linear model into practice and competitions in line with the Interacting Performance Theory as defined by O'Donoghue [33]. Specifically, this non-linear model allowed us to control for: (i) how performance was affected by a particular opponent (i.e., visual representation of strokes network); (ii) how the outcome of player's performances were influenced by quality and type of opposition (i.e., individual's performance described using one-mode projections); (iii) how the process of performances (points and strokes) were influenced by the quality and type of opposition (i.e., centrality of one-mode projection): and (iv) how different players were influenced by the same opponent in different ways (i.e., the use of identifiability measures). Others have also suggested that performance patterns in a racket sport like badminton should recognize and identify the key measures that best comprehend the player's characteristics based on their opponents with successful collaboration between scientists (performance analysts) and practitioners (coaches and players) essential [25,29–31]. The use of bipartite networks for badminton offers a novel perspective of performance analysis accounting for context (i.e., opponent-related performances) and applicability of results into practice.

4.1. Limitations of the proposed methodology

Some limitations of the current study need to be highlighted. Our model utilized only a fraction of the performance indicators traditionally used in badminton [23–25]. Therefore, the addition of other indicators, such as the type of serve, type of stroke or other contextual variables (e.g., match type, score-line or set), could possibly provide greater clarification of players' networks and their performance. Further, the network analysis was limited to specific outcome measures (e.g. centrality, etc.). Inclusion of other measures stated below could provide comprehensive information for coaches and players to enhance playing performance: the (Euclidean) distance covered between strokes and zones of the court during the point, the analysis of shuttlecock trajectories with Voronoi diagrams, the interplay between the number of strokes within a point, the speed of a player, and the fatigue status of players during the match.

In summary, the use of Network Science enabled the delineation of player's playing patterns (self- and opponent–related), based on stroke performance, during successful and unsuccessful points. In addition, the identifiability of each player's network and its associations with point outcome, provided a better understanding of stroke performances and individual features of badminton players. Therefore, the use of non-linear approaches (such as bipartite networks) to measure and visualize player's performances, accounting for the specific nature of badminton, may support coaches and players with the contextualized demands of playing patterns and their performances (i.e., winning and losing points).

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Data for reference

Data will not be publicly available, but any person interested in can require it writing the corresponding author via email.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

CRediT authorship contribution statement

Miguel–Ángel Gómez: Conceptualization, Methodology, Validation, Investigation, Resources, Data curation, Writing - original draft, Writing - review & editing, Visualization, Supervision, Project administration, Funding acquisition. **Fernando Rivas:** Methodology, Validation, Investigation, Resources, Data curation, Writing - review & editing. **Anthony S. Leicht:** Methodology, Writing - original draft, Writing - review & editing, Supervision. **Javier M. Buldú:** Conceptualization, Methodology, Software, Validation, Formal analysis, Data curation, Writing - original draft, Writing - review & editing, Visualization, Supervision, Project administration, Funding acquisition.

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