Faculdade de Desporto

Universidade do Porto

Centro de Investigação, Formação, Inovação em Desporto (CIFI$_2$D)

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Contributo da Análise de Redes Sociais, a partir da Centralidade de Autovetor, no estudo da performance desportiva em Voleibol de Alto Rendimento.

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Palavras-chave: ANÁLISE DE REDES SOCIAIS, CENTRALIDADE DE AUTOVERTOR, VOLEIBOL.

Dedicatórias,

Ao meu pai, minha inspiração;

À minha mãe, a força;

Ao meu irmão, a atitude;

Meu amor, minha vida.

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O estudo da Análise de Redes Sociais, entre as diversas utilidades, contribui para a análise das relações (humanas ou não). Relacionamento pode ser descrito como uma ligação afetiva, profissional ou de amizade entre pessoas perante algum objetivo ou interesse. Apesar dos relacionamentos serem assimétricos, quatro medidas Medidas de Centralidade são comumente utilizadas e revelam a influência e características dos componentes de uma Rede. Assim, vocês, de alguma forma ou de outra, foram importantes para construção deste trabalho, mas acima de tudo, para o meu desenvolvimento e formação do meu caráter.

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O conceito central desta metodologia revela que todos os relacionamentos definem quem somos e agimos (personalidade, educação, entre outro), assim uma *Rede* é construída através destas relações. Meu amor tu é a minha rede, onde tudo que eu faço e todos que estão ao meu redor não existiriam se não fosse por ti. Ninguém sabe o quanto sofri, batalhei, cresci, ganhei até chegar aqui como tu sabes. Sempre esteve ao meu lado segurando ou puxando minha mão para continuar, este resultado é tão teu quanto meu, **te amo Caroline**.

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Resumo

A otimização da performance nos Jogos Desportivos é um tema complexo e com múltiplas vias metodológicas para atingi-la. Dentre elas, a Análise de Redes Sociais contribui à Análise do Jogo utilizando de vias matemáticas advinda da Teoria dos Grafos, analisando a interação entre agentes numa rede. As Redes de Interação, mais utilizadas no campo desportivo, analisam a relação dos jogadores (unidades de análise ou nós) através dos passes (arestas). A presente tese expandiu o olhar dado às unidades de análise nos Jogos Desportivos e considerou as ligações diretas e indiretas entre as ações de jogo. Assim, o principal objetivo consistiu em verificar o comportamento de cada variável de jogo no voleibol, revelando assim o real papel de cada ação de jogo nos seis complexos de jogo; além da influência dos padrões de jogo para a eficácia das ações no voleibol feminino e masculino de alto nível. Os resultados sugerem que o facto de considerar as ações de jogo como unidades de análise fornecem importantes informações acerca da ecologia do jogo. Neste sentido, importantes padrões de jogo foram encontrados nos seis complexos de jogo, onde as ações realizadas em condições não-ideais (como as variáveis Condição de Distribuição, Zona e Tempo de Ataque) tiveram um papel central na maioria dos complexos analisados. As ações de jogo revelaram o mesmo comportamento independente do nível de eficácia considerado, indicando que a capacidade individual de solucionar os problemas de jogo assume um papel de maior importância do que o padrão de jogo em cada complexo. Em suma, a utilização de unidades não-agenciais, através da ponderação das ligações diretas e indiretas, forneceu informações refinadas e o peso do comportamento de cada variável em todos Complexos de Jogo contribuindo para o entendimento da ecologia e dinâmica do voleibol. Sugere-se, que futuras investigações considerem os sistemas táticos, características dos jogadores, ou ainda, fatores que possam impactar as ações individuais, como as restrições situacionais do jogo (momento, status da partida, ações prévias e posteriores ao erro).
PALAVRAS-CHAVE: Análise de Redes Sociais; Centralidade de Autovetor; Análise da Performance, Ações de jogo; Voleibol.

Abstract

The optimization of performance in Sports Games is a complex subject and with multiple methodological ways to reach it. Among them, Social Network Analysis contributes to Game Analysis using mathematical pathways derived from Graph Theory, analysing the interaction between agents in a network. The Interaction Networks, most used in the sports field, analyse the players relationship (units analysis or nodes) through the passes (edges). The present thesis expanded the look given to the analysis units in the Sports Games and considered the direct and indirect relation between the game actions. Thus, the main objective was to verify the behaviour of each game variable in volleyball, thus revealing the real role of each game action in the six Game Complexes; as well as the influence of game standards on the effectivity of high-level women's and men's volleyball. The results suggest that considering game actions as analysis units provides important insights into game ecology. In this sense, important game patterns were found in the six game complexes, where actions performed in non-ideal conditions (such as the Conditions of Distribution, Zone and Attack Tempo) played a central role in most of the complexes analysed. Game actions revealed the same behaviour regardless of the effectivity level considered, indicating that individual ability to resolve game problems shows a greater importance role than the play standard in each complex. In short, the use of non-agency units, through the weighting of direct and indirect connections, provided refined information and the weight of the behaviour of each variable in all Game Complexes, contributing to the understanding of the ecology and dynamics of volleyball. It is suggested that future investigations consider tactical systems, players characteristics, or factors that may impact individual actions, such as situational restrictions of the game (momentum, game status, previous and post-error actions).

KEY-WORDS: Analysis of Social Networks; Eigenvector Centrality; Performance Analysis, Game Actions; Volleyball.

Lista de Abreviaturas

AJ	Análise do Jogo
JD	Jogos Desportivos
ARS	Análise de Redes Sociais
SNA	*Social Network Analysis*
K	Complexo de Jogo
K0	Complexo de Jogo 0
KI	Complexo de Jogo I
KII	Complexo de Jogo II
KIII	Complexo de Jogo III
KIV	Complexo de Jogo IV
KV	Complexo de Jogo V
E0	Eficácia 0
E1	Eficácia 1
E2	Eficácia 2
GT	Graph Theory
TS	Team Sports
PA	Performance Analysis
USA	United State of America
OT	Others
IPS	Initial Position of Server
FC	First Contact
SC	Setting Condition
AZ	Attack Zone
AT	Attack Tempo
BO	Block Opposition
KIVB	Number of Available Player Before of Attack Coverage
KIVK	Number of Coverage Lines
KVD	Downball
KVF	Freeball

I. Introdução

1.1 Tema e pertinência do estudo

As pesquisas centradas na Análise do Jogo (AJ) nos Jogos Desportivos (JD) têm, entre seus principais objetivos, a otimização do processo de treino e o desenvolvimento de estratégias para a melhoria da eficiência e eficácia da equipa (Mesquita, Palao, Marcelino, & Afonso, 2013; O'Donoghue, 2009; Rink, 1993). A AJ emprega a observação das regularidades e particularidades dos acontecimentos, notação e interpretação dos dados (Hughes & Bartlett, 2002; Rui Marcelino, Sampaio, & Mesquita, 2011; O'Donoghue, 2014; O'Donoghue, Holmes, & Robinson, 2017). Neste sentido, a AJ pode utilizar uma abordagem centrada no jogador, i.e., focada nos elementos constituintes da equipa e suas interações (Clemente, Couceiro, Martins, & Mendes, 2014; Sasaki, Yamamoto, Miyao, Katsuta, & Kono, 2017), ou uma abordagem centrada no jogo (Hurst et al., 2016; Loureiro et al., 2017), i.e., focada nas ações de jogo *per se* e no fluxo de jogo.

A investigação utilizando a AJ inclui, desde a sua origem, três macro tipos de análise: descritiva, comparativa e preditiva (Marcelino et al., 2011). A Análise Descritiva está relacionada com a observação cumulativa de medidas globais de rendimento, identificando, descrevendo e caracterizando-a. Alguns autores utilizaram este tipo de análise para identificar e caracterizar as movimentações ofensivas e defensivas em seleções femininas de voleibol (Jäger & Schöllhorn, 2007); além disso, a Análise Descritiva foi empregada para examinar padrões de movimento (*sprinting*, corridas média e baixa intensidade) dos jogadores no futsal masculino de alto nível (Castagna, D'Ottavio, Vera, & Álvarez, 2009).

A Análise Comparativa pretende observar indicadores de rendimento predominantemente em função de posições funcionais dos jogadores, níveis competitivos e sistemas de pontuação e as diferenças em função do género. A título de exemplo, Jäger and Schöllhorn (2007) evidenciou as diferenças entre os movimentos dos jogadores de defesa e de ataque no voleibol feminino; Já Lupo, Tessitore, Minganti, and Capranica (2010) verificaram as diferenças em parâmetros físicos-técnicos (frequência de ações realizadas pelos jogadores, números de jogadores envolvidos e passes, entre outros) entre três níveis competitivos no Pólo Aquático.

Por sua vez, a Análise Preditiva tem vindo a avançar para a explicação de indicadores de rendimento e resultados finais em competição, fundamentalmente, em função de variáveis situacionais como: *match status*, qualidade de oposição e local da prova (Rui Marcelino et al., 2011). Pesquisas tentando predizer o resultado do jogo através de um evento recorrente (*match status*) foram utilizadas no futebol masculino para verificar as diferenças em manter a posse de bola em diferentes situações do marcador (a perder, a empatar e a ganhar), indicando que as equipas que estão “a perder” o jogo possuem maior posse de bola que as demais situações; além disso, os estudos envolvendo a vantagem de jogar em casa (*home advantage*) tem revelado que as equipas que jogam no seu local de jogo vencem 50% mais os jogos disputados fora de casa em calendários equilibrados (Courneya & Carron, 1992).

No voleibol, Mesquita et al. (2013) apontam tendências de investigação da AJ, em que a Análise Descritiva se baseou na identificação de indicadores táticos-técnicos, através de dados acumulados em diferentes ações de jogo em função dos seus efeitos; como por exemplo, pontos de serviço, percentagem de erros de ataque, entre outros (Castro & Mesquita, 2010). A Análise Correlacional, com o propósito de identificar relações entre diferentes conjuntos de ações, tem como principal objetivo entender como um indicador de jogo pode refletir nas ações posteriores ocorridas; por exemplo, como a zona e o tipo de distribuição podem afetar a eficácia de ataque, ou ainda, a influência da receção ou defesa na eficácia de ataque (Afonso, Mesquita, Marcelino, & Silva, 2010; Araújo et al. 2011; Lais & Kountouris 2010). Já as Análises Preditivas centram-se na tentativa de predizer o desempenho e a influência das ações no resultado do jogo. Por exemplo, as ações de jogo mais estudadas são: o serviço, a receção, a distribuição, o ataque, cabendo salientar que a ação de ataque foi a de maior influência para prever o sucesso da equipa (Marcelino & Mesquita, 2008; Marelić, Rešetar, & Janković, 2004; Zetou, Moustakidis, Tsigilis, & Komninakidou, 2007)

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Entretanto, uma das maiores limitações dos estudos na área do JD através da AJ tem a ver com a dificuldade em considerar a característica sistémica do jogo, aliada à ênfase na procura de relações "lineares" entre as variáveis, restringindo a validade ecológica dos estudos (Lames & McGarry, 2007; Marcelino et al., 2011), não obstante tornar mais simples as análises efetuadas. Assim, independentemente do tipo de análise efetuada, ressalta-se que os estudos dos JD a partir da AJ tem evoluído na medida em que necessita cada vez mais de indicadores de desempenho que respeitem a ecologia do jogo (Clemente, Martins, Mendes, & Silva, 2016; Memmert, Lemmink, & Sampaio, 2017; Paulo, Davids, & Araújo, 2018), mesmo que a complexidade acrescida coloque desafios à recolha e interpretação dos dados. Tal aporte fornece uma visão global do jogo, sem negligenciar as suas partes e o peso das ações no jogo, assim como descodifica interessantes padrões de comportamento (Marcelino & Sampaio, 2015), na tentativa de considerar a visão do jogo como um sistema dinâmico capaz de se auto-organizar perante os constrangimentos que o próprio envolvimento e o próprio sistema e subsistemas aportam (McGarry, Anderson, Wallace, Hughes, & Franks, 2002; Thelen, 2005; Walter, Lames, & McGarry, 2007).

A teoria dos sistemas dinâmicos tem vindo a contribuir para o estudo dos JD ao explicar algumas regularidades de padrões emergentes dentro de um sistema baseado na auto-organização e inter-relação dos seus subsistemas (Hanken, 1983; McGarry et al., 2002; Walter et al., 2007). Apesar da complexidade da análise das partes ao apresentarem uma independência "parcial" do sistema global (Gréhaigne, Bouthier, & David, 1997; Thelen, 2005), é possível realizar uma análise topológica das estruturas emergentes, procurando uma compreensão do comportamento global sistémico (Loureiro et al., 2017). Tal tem contribuído para um melhor entendimento das relações entre equipas/jogadores (Ciuffarella et al., 2013; Dutt-Mazumder, Button, Robins, & Bartlett, 2011; Rabaz, Castuera, Arias, Domínguez, & Arroyo, 2013) e, consequentemente, para a otimização do processo de treino e a criação de estratégias de jogo (Lames & McGarry, 2007; McGarry, 2009).

Portanto, a utilização de métodos de análises sistémicas – tanto de caráter qualitativo quanto quantitativo, respeita a complexidade dos JD e, por isso, são decisivas para uma cabal compreensão do jogo, respeitando a sua lógica acontecimental e contribuindo, por via disso, na construção de processos de preparação desportiva eficazes.

Neste enquadramento, a Análise de Redes Sociais (ARS, ou ainda, SNA do termo inglês *Social Network Analysis*), centrada em analisar o comportamento e a interação dos elementos ou unidades de um sistema (Borgatti, Everett, & Johnson, 2013; Freeman, 2004; Quatman & Chelladurai, 2008; Wasserman & Faust, 1994) tem vindo a evidenciar-se como uma ferramenta interessante no estudo da AJ nos JD. Ao captar informações de todo o sistema, a ARS auxilia no desvendar de padrões importantes, fornecendo, assim, uma visão ecológica do jogo e uma compreensão da estrutura, dinâmica e interação dos elementos pertencentes a todo o sistema (Passos et al., 2011). Não constitui surpresa que venha sendo adotada como forma de AJ (Clemente et al., 2016; Dey, Ganguly, & Roy, 2017; Fewell, Armbruster, Ingraham, Petersen, & Waters, 2012; Grund, 2012; Hurst et al., 2016).

A ARS surgiu na década de 1930, procurando responder a questões de pesquisa da Sociologia e da Psicologia, de forma que avanços na teoria sociológica, na matemática e na computação ajudaram as análises sociométricas simplistas iniciais a evoluírem para uma abordagem metodológica mais sofisticada resultante nas Análise de Redes Sociais (Freeman, 2004; Quatman & Chelladurai, 2008).

Alicerçada na teoria dos Grafos (Wäsche, Dickson, Woll, & Brandes, 2017), a ARS tem a vantagem de investigar os padrões estatísticos de interação do comportamento entre os agentes ou elementos de um sistema (Borgatti, Everett, & Johnson, 2013; Freeman, 2004; Quatman & Chelladurai, 2008; Wasserman & Faust, 1994). Neste contexto, um grafo é criado para contribuir na visualização da estrutura, dinâmica, relação e interação entre os agentes (Clemente, Martins, & Mendes, 2015; Passos et al., 2011; Wasserman & Faust, 1994). Os agentes, por sua vez, denominados de nós (*nodes*), quando assumem algum tipo de relação proporcionam a criação de uma aresta (*egde*) (Wäsche et al., 2017), a qual, através de um conjunto de métricas ou Medidas de Centralidade, contribui para a obtenção de respostas às diferentes influências que os agentes causam aos demais, ou ao sistema como um todo.

Entretanto, o estudo da ARS não se limita apenas ao estudo das relações sociais humanas, isto é, a interação entre agentes já foi utilizada em diversos campos da ciência afim de descortinar informações sobre relações sistémicas significativas, como: a atração gravitacional entre os planetas no sistema solar; a interação química de diversos átomos para formar diferentes tipos de moléculas; a interação entre componentes eletrónicos (capacitadores e resistores) no fluxo de uma corrente num circuito; e a interação entre as espécies num ecossistema (Freeman, 2004). Neste sentido, a ARS, por estar fundamentada na Teoria dos Grafos, possibilita a utilização de diferentes unidades de análise, onde diferentes compreensões de elementos e relações do sistema podem ser assumidas dependendo da questão de pesquisa a ser respondida (Ortiz-Pelaez, Pfeiffer, Soares-Magalhaes, & Guitian, 2006).

Sugerido por Wäsche et al. (2017), dentro dos fenómenos sociais desportivos, o estudo das redes pode obedecer a uma tipologia conceitual levando em conta seis tipos diferentes de redes, sendo elas: (i) *Redes de Competição* analisam diferentes eventos (intereventos) exibindo padrões estruturais e de desempenho dos atletas e/ou equipas (ver Bothner, Kim, and Smith (2012); Breznik and Batagelj (2012); Jessop (2006); Mukherjee (2012); Radicchi (2011); Saavedra, Powers, McCotter, Porter, and Mucha (2010); Sanders (2011); (ii) *Redes de Interorganização* verificam as relações entre organizações, ligas, franquias, clubes, entre outros (ver Cobbs (2011); Cousens, Barnes, and MacLean (2012); Sallent, Palau, and Guia (2011); Seevers, Skinner, and Dahlstrom (2010); (iii) *Redes de Intraorganização* exprimem características internas das organizações e o impacto destas no desempenho desportivo, como: em conflitos sociais, em relações de amizade e de confiança, na eficácia dos membros de um clube, em eleições de presidentes e conselheiros (Warner, Bowers, & Dixon, 2012; Zachary, 1977); (iv) *Redes de Afiliação* unem as Redes Intra e Interorganizacionais considerando os indivíduos nas organizações e a participação dos mesmos em eventos (Hambrick, 2012); (v) *Ambientes Sociais* levam em consideração como as redes sociais *online* (p.e. *Twitter*) afetam e moldam o comportamento dos jogadores, ou ainda, a comunicação dos organizadores de eventos com os seus seguidores (ver Hambrick, 2012); e (vi) *Redes de Interação*, ao serem as mais utilizados na AJ, têm considerado sobretudo a interação entre jogadores de uma equipa com base no desempenho dos jogadores e nas regras do jogo. Alguns estudos consideraram os passes entre jogadores (como nós) realizados no futebol (Duch, Waitzman, & Amaral, 2010; Grund, 2012), no basquetebol (Fewell et al., 2012) e no polo aquático (Passos et al., 2011).

Na última década, os estudos da ARS atraíram o interesse do desporto, revelando não só as relações significativas entre os jogadores (Yamamoto & Yokoyama, 2011), como também informações do comportamento entre todos os participantes do jogo (como a colaboração, a coesão, os papéis e as hierarquias entre os jogadores) (Ribeiro, Silva, Duarte, Davids, & Garganta, 2017).

Neste sentido, as Medidas de Centralidade têm vindo a ser as mais utilizadas e revelam a posição ou importância funcional dos agentes na rede. Através dos padrões de ligação (podendos ser diretas a um determinado nó ou indiretas através de ligações de segundo ou terceiro nível), revelam vantagens ou desvantagens de cada nó, no cenário no qual estão inseridas (Borgatti, 2005; Wäsche et al., 2017; Zuo et al., 2011). Entre as principais Medidas de Centralidade destaca-se a Medida de Grau, de Intermediação, Proximidade e Autovetor (Borgatti, 2005; Freeman, 1979; Ramos, Lopes, & Araújo, 2017; Ribeiro et al., 2017) .

A Centralidade de Grau (do termo inglês *degree*) pode subdividir-se em Grau de Entrada (*in-degree*), que permite identificar o nó que recebe mais ligações, e, ainda, Grau de Saída (*out-degree*), que permite identificar o nó que direciona mais ligações, como por exemplo, identificação do jogador que recebeu ou efetuou mais passes no jogo. A Centralidade de Intermediação (*Betweenness*) é revelada através das relações indiretas de um nó com outros dois, ou seja, representa o quanto cada jogador contribuiu como intermediário entre outros jogadores. Esta medida, por exemplo, pode revelar a responsabilidade que um determinado jogador tem dentro de um setor do jogo.

Já a Centralidade de Proximidade (C*loseness*) soma a distância de todos os caminhos mais curtos de um nó a outro na rede. Esta medida fornece informações, por exemplo, sobre a adjacência de um jogador a outro (Borgatti, 2005; Freeman, 1979; Ribeiro et al., 2017; Wäsche et al., 2017).

A Centralidade de Autovetor (*Eigenvector*) (Bonacich, 1987, 2007), constitui um dos pilares deste trabalho e é considerada uma medida de *status* (Bonacich & Lloyd, 2001), onde as ligação diretas e indiretas são consideradas e podem ser revisitadas várias vezes pelos nós e arestas (Borgatti, 2005). Ao fornecer a contribuição e o papel relativo de cada agente dentro do sistema global (Bonacich, 1987, 2007; Ramos et al., 2017; Wasserman, 1994), esta medida constitui uma poderosa ferramenta da ARS para o estudo da AJ nos JD, na medida em que pondera a interação entre todos os agentes do sistema e revela as que são mais importantes no jogo (Afonso, Laporta, & Mesquita, 2017; Hurst et al., 2017; Loureiro et al., 2017).

A maioria dos estudos empregando a ARS, no domínio dos JD, têm empregado uma abordagem centrada na interação entre os jogadores, utilizando-os como unidade de medida (nós) (Ramos et al., 2017) em diversos desportos e envolvendo objetivos e medidas diferentes. A título de exemplo, alguns autores analisaram a estruturação ofensiva no futebol utilizando a Centralidade de Grau (entrada e saída), Intermediação, Proximidade e Autovetor através da relação do passe entre jogadores (ver Alves, Gonçalo, José, Vasco, & Miguel (2018); Aquino et al. (2018); Malta and Travassos (2014); no Râguebi utilizou-se a centralidade de autovetor para avaliar as ações defensivas (Sasaki et al., 2017); no Basquetebol elucida-se a contribuição de cada jogador na fase de ataque através do recurso à Centralidade de Grau (entrada e saída) (Clemente, Martins, Kalamaras, & Mendes, 2015); no Cricket analisou-se, através da Centralidade de Intermediação, Proximidade e Grau, a criação de uma equipe internacional (Dey et al., 2017).

No voleibol, alguns pesquisadores têm retirado o foco da análise centrada nos jogadores e utilizado uma abordagem centrada no jogo, considerado os nós como ações de jogo ocorridas em diferentes Complexos de Jogo (K), tanto no voleibol masculino como no feminino de alto nível (Hurst et al., 2017; Hurst et al., 2016; Loureiro et al., 2017). Os Complexos de jogo são fases ou compartimentos que subdividem o jogo, sendo eles: Complexo 0 (K0) ou serviço; Complexo I (KI) ou *Side-out*; Complexo II (KII) ou contra-ataque (*Side-out Transition*); Complexo III (KIII) ou contra-ataque do contra-ataque (*Transition of Transition)*; Complexo IV (KIV) ou Proteção de ataque; e Complexo V (KV) ou Bola Morta (*Freeball* ou Downball) (Adaptado de Monge, 2003, 2007). Estes estudos utilizaram a Centralidade de Autovetor e foram preliminares, funcionando como estudos-piloto para verificar a funcionalidade desta ferramenta no estudo do comportamento das ações de jogo. Entretanto, nota-se que estes estudos analisaram apenas alguns Complexos de Jogo e não a sua globalidade, não considerando, por isso, a ecologia do jogo de forma íntegra. Ademais, a eficácia das ações e das jogadas não foi considerada nestas análises.

1.1 Objetivo do estudo

O recurso da ARS e a possibilidade de considerar unidades de análise para além dos jogadores (por exemplo, ações de jogo), baseia-se no entendimento que esta perspetiva possui pertinência, adequação e potencial para aceder a uma visão sistémica e ecológica dos JD (McGarry, Anderson, Wallace, Hughes, & Franks, 2002). Este olhar sistémico do voleibol ainda não foi considerado, em sua totalidade, envolvendo uma análise interacional das ações de jogo entre todos os Complexos de Jogo, como também, ainda não foi desvendado a influência dos padrões de jogo na eficácia das ações.

Assim, os objetivos do presente trabalho visam: (i) avançar com o estudo da ARS indicando uma expansão da potencialidade de se considerar unidades de análise não-agenciais nos JD; (ii) verificar a importância de considerar as ligações diretas e indiretas para a análise do comportamento de cada variável de jogo no voleibol, revelando assim o verdadeiro papel de cada ação de jogo nos seis complexos de jogo; (iv) examinar a influência dos padrões de jogo resultantes da interação entre todos os complexos de jogo, para a eficácia das ações no voleibol feminino e masculino de alto nível.

1.2 Estrutura da dissertação

A presente tese foi organizada e estruturada de forma a que cada artigo contribuísse para responder a cada um dos objetivos referenciados anteriormente. Neste sentido, o Capítulo I justifica e legitima a presente dissertação apresentando uma breve introdução dos principais aspetos que dizem respeito à utilização da ARS nos JD e, ainda, uma conceituação dos principais termos da ARS (por exemplo, Grafo, unidades de análise ou nós, arestas, medidas de centralidades, entre outros),

No Capítulo II é apresentado o primeiro ensaio teórico da tese (ver Tabela 1), onde são destacados conceitos e abordagens já utlizados na ARS nos JD, bem como o foco que vem sendo dado à utilização desta ferramenta, principalmente no voleibol. Além disso, este ensaio teórico expõe uma expansão da tipologia de unidades de análise adotadas frequentemente nos JD (centrados sobretudo nos jogadores), para uma centrada em unidades *não-agenciais* (ações de jogo) sugerindo caminhos de relevo a trilhar por investigações futuras.

O capítulo III é composto pelos quatro artigos empíricos que compõe esta dissertação, onde os conceitos desenvolvidos no artigo teórico são aplicados no contexto do voleibol masculino e feminino de alto nível. Neste âmbito, o primeiro artigo objetivou examinar as diferenças funcionais e a interação entre todos os Complexos de Jogo existentes no voleibol feminino de alto nível, a partir da perspetiva da ARS, com base na Centralidade de Autovetor. Já o segundo artigo empírico tratou de analisar a interação das ações de jogo dos seis Complexos de Jogo no voleibol de alto nível no masculino, através da centralidade de autovetor.

O terceiro e o quarto estudo empíricos, ponderam as ligações indiretas, através da Centralidade de Autovetor, para compreender os padrões de jogo das ações, bem como a influência que os mesmos teriam na eficácia final em cada complexo de jogo. Nesse sentido, o terceiro estudo investigou o problema relatado anteriormente utilizando como amostra o voleibol feminino de alto nível, enquanto que o alvo do quarto artigo foi o voleibol masculino de alto nível.

Por fim, o Capítulo IV procurou destacar os resultados obtidos em cada artigo, discutindo seus principais achados. Além disso, pretendeu apontar caminhos à investigação na Análise do Jogo nos JD a partir da ARS, pretendendo contribuir para que menos lacunas perdurem futuramente nesta temática.

Tabela 1. Estrutura dos artigos que compõe a presente tese.

Nº	Nome	Revista	Situação
I	Contributo da Análise de Redes Sociais para a Análise do Jogo: Breve sinopse concetual e sinóptica	Revista Portuguesa de Ciências do Desporto	Submetido
II	Interaction network analysis of the six game complexes in high-level volleyball through the use of Eigenvector Centrality	PLOS One	Publicado
III	The need for weighting indirect connections between game variables: Social Network Analysis and eigenvector centrality applied to high-level men's volleyball	*International Journal of Performance Analysis in Sport*	Publicado
IV	Do distinct game patterns influence play efficacy in high level women's volleyball? A study using Eigenvector Centrality	*Kinesiology Journal*	Submetido
V	Using social network analysis to link game patterns and play efficacy. A study in high-level men's volleyball	*Frontiers in Psychology*	Em fase de Submissão

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II. Ensaio Teórico

Contributo da Análise de Redes Sociais para a Análise do Jogo: Breve sinopse concetual e sinóptica[1]

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Contributo da Análise de Redes Sociais para a Análise do Jogo: Breve sinopse concetual e sinóptica

RESUMO

Na tentativa de melhor responder aos complexos problemas emergentes da performance desportiva, a Análise de Jogo vem explorando diversas metodologias. De entre estas, a Análise de Redes Sociais vem ocupando um espaço crescente na análise de jogo aplicada aos Jogos Desportivos, que podem ser analisados com redes de interação. Com raiz matemática na Teoria dos Grafos, a Análise de Redes Sociais permite analisar as relações entre diferentes unidades de análise. As pesquisas em desporto têm utilizado, maioritariamente, os jogadores enquanto unidade de análise (nós). Recentemente, verificou-se uma promissora expansão para a análise de ações de jogo enquanto nós. Contudo, pela complexidade de interações entre as unidades de análise e suas consequências, as relações indiretas entre estas deverão ser ponderadas e, neste sentido, a escolha da métrica mais apropriada é decisiva. Análise de Redes Sociais alcança este propósito através da Centralidade de Autovetor, cuja utilização vem emergindo no contexto de Jogos Desportivos. Todavia, as pesquisas tendem a analisar somente certas fases ou momentos do jogo ou, alternativamente, condensando-os e, com isso, perdendo informação acerca da sua especificidade. Em suma, apesar das promissoras avenidas, carece a aplicação duma abordagem sistémica para analisar as interrelações do jogo na sua complexidade e especificidade funcional.

Palavras-chave: Análise da Performance, Análise do Jogo, Centralidade de Autovetor, Ações de Jogo, Análise Sistémica.

ABSTRACT

In an attempt to better respond to the complex problems emerging from sports performance, Game Analysis has been exploring several methodologies. Among these, Social Network Analysis has been occupying a growing space in the game

analysis applied to the Sports Games, which can be analyzed with Interaction Networks. With a mathematical root in Graph Theory, Social Networks Analysis allows analyzing relations between different analysis units. Sports research have mostly used players as the analysis unit (nodes). Recently, there has been a promising expansion for the analysis of game actions while nodes. However, because of the interactions complexity between the analysis units and their consequences, the indirect relationships between them should be weighed and, in this sense, the choice of the most appropriate metric is decisive. Social Network Analysis achieves this purpose through the Autovetor Centrality, whose use has been emerging in the context of Sports Games. However, surveys tend to analyze only certain phases or game moments or, alternatively, condense them and thereby lose information about their specificity. In short, in spite of the promising avenues, it is necessary to apply a systemic approach to analyze the interrelationships of the game in its complexity and functional specificity.
Keywords: Performance Analysis, Game Analysis, Eigenvectors Centrality, Game Actions, Systemic Analysis.

1. INTRODUÇÃO

A análise da performance nos Jogos Desportivos (JD) constitui um tema profundamente complexo e que tem motivado uma diversidade correspondente de abordagens, da qual iremos destacar a Análise do Jogo (AJ). A AJ busca analisar o fenómeno da performance desportiva de diferentes óticas. Nos últimos anos, as abordagens sistémicas, respeitadoras da complexidade dos JD, vêm assumindo um lugar de relevo (Lames & McGarry, 2007; Lebed, 2006; McGarry, Anderson, Wallace, Hughes, & Franks, 2002; Thelen, 2005). Todavia, a representação e avaliação das múltiplas interações entre inúmeras variáveis não constitui um problema de fácil resolução. Neste âmbito, distintas metodologias vêm tentando capturar esta complexidade, e.g.: Análises Descritivas (Castro & Mesquita, 2010); Qui-quadrado (Laporta, Nikolaidis, Thomas, & Afonso, 2015); Análises Preditivas (Marcelino, Mesquita, & Sampaio, 2011), Regressão Logística Multinominal (Afonso & Mesquita, 2011); Análise da Função Discriminante (Sampaio, Lago, Gonçalves, Maçãs, & Leite, 2014), Análise

Sequencial de Retardos (Afonso, Mesquita, Marcelino, & Silva, 2010) e Análise de Clusters (Sankaran, 2014).

Neste contexto, a Análise de Redes Sociais (ARS) constitui uma poderosa e promissora ferramenta para auxiliar na resposta aos problemas abordados pela AJ. Emergente da Psicologia e da Sociologia (Freeman, 2004), o objetivo primordial consiste em desvendar os comportamentos dos atores, emergentes das suas interações (Borgatti, Everett, & Johnson, 2013; Wasserman & Faust, 1994). Assim, alicerçada na teoria dos Grafos (Wäsche, Dickson, Woll, & Brandes, 2017), padrões estatísticos de interação do comportamento entre elementos de um sistema são verificados (Borgatti, Everett & Johnson, 2013; Freeman, 2004; Quatman & Chelladurai, 2008b; Wasserman & Faust, 1994). A utilização da ARS nas Ciências do Desporto vem assumindo maior preponderância nas últimas décadas, pois auxilia na busca de padrões nos fluxos de jogo (Wäsche, Dickson, Woll, & Brandes, 2017).

A ARS possibilita a consideração de diferentes tipos de unidades de análise. Apesar dos jogadores constituírem a unidade de análise mais usual nas pesquisas com ARS em desporto (e.g. Clemente, Martins, Kalamaras, & Mendes (2015); Malta & Travassos (2014); Sasaki, Yamamoto, Miyao, Katsuta, & Kono (2017), vem-se observando uma expansão do tipo de unidades de análise utilizados no desporto (e.g., Hurst, Loureiro, Valongo, Laporta, Nikolaidis, & Afonso (2017); Hurst, Loureiro, Valongo, Laporta, Nikolaidis, & Afonso (2016); Loureiro, Hurst, Valongo, Nikolaidis, Laporta, & Afonso (2017). Conforme iremos analisar, tais abordagens vêm expandindo o âmbito de utilização das ferramentas da ARS no desporto, nomeadamente incrementando a profundidade e diversidade de perspetivas de tratamentos conferidos a problemas emergentes.

Além das diferentes possibilidades de escolha relativamente à unidade de análise, a ARS engloba um conjunto alargado de ferramentas matemáticas, permitindo a seleção de diferentes métricas (Freeman, 1978). Cada métrica apresenta potencialidades e limitações distintas, pelo que a sua escolha deverá estar profundamente dependente do problema de estudo. No âmbito das Ciências do Desporto, as métricas de centralidade realçam os agentes mais influentes em determinado conjunto de interações (Borgatti, 2005; Ramos, Lopes, & Araújo, 2017; Ribeiro, Silva, Duarte, Davids, & Garganta, 2017). Todavia, a maioria destas métricas apenas considera as ligações diretas entre unidades de análise (p.e., Centralidade de Grau, Borgatti (2005); Freeman (1978). Existem, porém, métricas que consideram as ligações indiretas no estabelecimento dos pesos de centralidade atribuídos a cada unidade de análise (p.e., Centralidade de Autovetor, Bonacich (2007); Bonacich & Lloyd (2001).

O presente ensaio visa elucidar o enfoque que vem sendo dado na utilização da ARS nos JD, realçando potenciais avenidas de pesquisa ainda por explorar. Em particular: (i) perscrutando a potencial expansão da tipologia de unidades de análise adotada; (ii) analisando as potencialidades de se pesarem as interações indiretas em adição às diretas, na busca duma análise mais completa dos fenómenos investigados; e (iii) sugerindo caminhos de relevo a trilhar por investigações futuras.

2. CONCEITOS BASILARES DA ANÁLISE DE REDES SOCIAIS

Sinopse histórica e tipologia de redes

Alicerçada na matemática formal, a ARS emergiu na década de 1930, advinda da Sociologia e Psicologia e impulsionada pelos desenvolvimento metodológicos e computacionais (Freeman, 2004). Baseada em técnicas e métricas adaptadas da Teoria dos Grafos (Wäsche, Dickson, Woll, & Brandes, 2017), a ARS permite descobrir padrões de interação do comportamento relacional entre atores (Freeman, 2004; Quatman & Chelladurai, 2008b), auxiliando na compreensão da sua estrutura, função, interação e dinâmica destes elementos dentro de um sistema (Passos, Davids, Araujo, Paz, Minguéns, & Mendes, 2011). A raiz matemática da Teoria dos Grafos possibilita expandir as unidades de análise da ARS, que não necessita de ficar limitada a agentes, conforme será explorado neste ensaio. Desta forma, através de uma perspetiva relacional, torna-se pertinente a utilização desta metodologia no campo desportivo (Grund, 2012; Ribeiro, Silva, Duarte, Davids, & Garganta, 2017; Wäsche, Dickson, Woll, & Brandes, 2017).

Diversos tipos de redes podem ser estabelecidos com recurso à ARS. Num trabalho seminal, Wäsche, Dickson, Woll, & Brandes (2017) organizaram uma categorização da literatura existente a respeito da ARS no desporto. Os resultados permitiram desenvolver uma tipologia conceitual deste campo de pesquisa, elucidando seis tipos diferentes de redes utilizadas: Redes de Competição, Redes de Interorganização, Redes de Intra-organização, Redes de Afiliação, Ambientes Sociais e Redes de Interação.

As Redes de Competição são caracterizadas pela análise de diferentes eventos (intereventos), onde os padrões estruturais e o desempenho de atletas ou equipes desportivas são fornecidos através de resultados de jogos, competições, entre outros. Os autores ainda mencionam que uma possibilidade de aplicação da ARS poderia ser o cálculo de probabilidades de apostas (ver Bothner, Kim, & Smith (2012); Breznik & Batagelj (2012); Jessop (2006); Mukherjee (2012); Radicchi (2011); Saavedra, Powers, McCotter, Porter, & Mucha (2010); Sanders (2011).

Redes de Interorganização analisam as relações estruturais entre organizações como, por exemplo, associações desportivas, ligas, clubes. Os autores subdividiram ainda em dois domínios: Gestão Desportiva e Literatura relacionada ao Desporto. Os estudos relacionados ao gerenciamento desportivo levaram em conta a relação entre entidades desportivas (ver Cobbs (2011); Cousens, Barnes, & MacLean (2012); Sallent, Palau, & Guia (2011); Seevers, Skinner, & Dahlstrom (2010), enquanto que a literatura desportiva[2] relacionou os artigos científicos através das citações destes estudos (ver Agulló-Calatayud, González-Alcaide, Valderrama-Zurián, & Aleixandre-Benavent (2008); Bruner, Erickson, Wilson, & Côté (2010); Love & Andrew (2012); Quatman & Chelladurai (2008a).

Já as Redes de Intraorganização revelam as características de dentro das organizações. Apesar dos poucos estudos nesta temática, eles revelaram aspetos como conflitos sociais, relações de amizade e de confiança, eficácia dos

[2] Os autores mencionam que este tipo de categorização poderia ser um novo tipo de rede, porém consideraram como Redes Interorganizacionais pois os grupos de autores, ou autores individuais, são também organizações sociais.

membros de um clube, o relacionamento destes aspetos com o impacto no desempenho desportivo (Warner, Bowers, & Dixon, 2012; Zachary, 1977). Além disso redes onde as trocas de informações táticas, informações a respeito da eleição de presidentes e conselheiros desportivos, também fazem parte deste tipo de redes.

As Redes de Afiliação compreendem os dois tipos de redes citadas anteriormente (intra e interorganizacionais), pois consideram indivíduos nas organizações e a participação de atores em eventos. Além disso, pode-se incluir uma rede que leve em conta a diretoria de um clube desportivo, bem como redes corporativas relacionada com patrocínios e com a interatividade entre atletas (Hambrick, 2012).

Ambientes Sociais são redes dedicadas aos ambientes no qual os indivíduos estão inseridos, ou seja, no caso do desporto, como as redes sociais online (*Twitter*) influencia o comportamento dos atores e também é moldado por eles, considerando a comunicação dos organizadores de eventos desportivos e de seus seguidores (ver Hambrick (2012). Além disso, ARS pode ser aplicada para entender a influencia do Ambiente Social na participação desportiva, no *doping* ou nas lesões dos atletas.

E por fim, as Redes de Interação, que, diferentemente das Redes de Competição, consideram a interação entre jogadores dentro de uma equipe, isto é, são caracterizadas por conter relações baseadas nas regras do jogo e no desempenho dos jogadores dentro de uma equipe, como por exemplo a relação dos atletas através dos passes realizados no futebol (Duch, Waitzman, & Amaral, 2010; Grund, 2012), no basquete (Fewell, Armbruster, Ingraham, Petersen, & Waters, 2012) e de jogadores de polo aquático (Passos, Davids, Araujo, Paz, Minguéns, & Mendes, 2011). Os autores reforçam quem este tipo de rede e as redes de competição são específicas no âmbito desportivo, enquanto que as outras são importantes para outros contextos sociais com os mesmos tipos de nós e relações.

Unidades de análise e métricas

No contexto da ARS, as unidades básicas de observação de uma rede são designadas por nós (Brass, Galaskiewicz, Greve, & Tsai, 2004). Os nós relacionam-se uns com outros, formando ligações que são designadas por arestas (Wäsche, Dickson, Woll, & Brandes, 2017). As arestas podem representar distintos tipos de relações determinadas pelo problema de estudo. Por exemplo, os jogadores podem-se relacionar através dos passes, os funcionários de uma empresa através de relações de empatia, as células pela interação molecular, entre outros (Barabasi & Oltvai, 2004; Bode, Wood, & Franks, 2011; Passos, Davids, Araujo, Paz, Minguéns, & Mendes, 2011). No conjunto, os nós e arestas fornecem características do comportamento de todo ambiente (Freeman, 2004; Quatman & Chelladurai, 2008b).

Embora a ARS tenda a considerar os agentes como unidades de análise (Grund, 2012; Ribeiro, Silva, Duarte, Davids, & Garganta, 2017; Wäsche, Dickson, Woll, & Brandes, 2017), a sua raiz na Teoria dos Grafos possibilita a exploração de unidades de análise não-agenciais. Por exemplo, segundo Ortiz-Pelaez, Pfeiffer, Soares-Magalhaes, & Guitian (2006), a definição de elementos e suas relações depende da questão a ser pesquisada e respondida, pois os nós podem assumir diversas tipologias (p.e., atletas, propriedades, animais, vizinhanças, entre outros). Com efeito, alguns pesquisadores ampliaram já a utilização desta ferramenta e consideraram a interconexão de ações[3] como nós e a relação entre estas ações como as arestas (Afonso, Laporta, & Mesquita, 2017; Hurst, Loureiro, Valongo, Laporta, Nikolaidis, & Afonso, 2017; Hurst, Loureiro, Valongo, Laporta, Nikolaidis, & Afonso, 2016; Loureiro, Hurst, Valongo, Nikolaidis, Laporta, & Afonso, 2017). De resto, o valor de centralidade não considera o tipo de unidade de análise selecionada, mas somente a ponderação das interrelações estabelecidas.

A ASR apresenta um diversificado conjunto de métricas, cada uma com potencialidades e limitações específicas. Deste modo, uma clara definição do problema de estudo é essencial, determinando o tipo de métricas mais ajustáveis. Destaque para as métricas de Centralidade, que avaliam a posição

[3] Ações de jogo foram consideradas como a unidade básica de análise em cada Complexo de jogo, assim os jogadores realizam-nas na busca de marcar um ponto, ou dificultar as ações adversárias.

ou a importância funcional dos elementos, e, dependendo da medida, podem estar associadas a diferentes vantagens ou desvantagens para os atores (Wäsche, Dickson, Woll, & Brandes, 2017; Zuo, Ehmke, Mennes, Imperati, Castellanos, Sporns, & Milham, 2011). Estas métricas revelam a importância de cada unidade de análise (nó) na rede (Borgatti, 2005). De entre esta classe de métricas, quatro Centralidades são comumente utilizadas: Grau, Intermediação, Proximidade e Autovetor (Freeman, 1978; Ribeiro, Silva, Duarte, Davids, & Garganta, 2017). A Centralidade de Grau considera o número de ligações diretas entre nós. A Centralidade de Intermediação pesa o número de vezes que um nó se conecta a dois outros nós através de seus caminhos mais curtos. A Centralidade de Proximidade considera o somatório das distâncias de todos os caminhos mais curtos de um nó a outro em um gráfico.

Destaca-se a Centralidade de Autovetor (*Eigenvector*) de Bonacich (Bonacich, 1987, 2007), conhecida como uma medida de *status* (Bonacich & Lloyd, 2001), a qual prevê que as trajetórias podem revisitar nós e arestas várias vezes ao longo do caminho (Borgatti, 2005). Assim, enquanto a métrica de Grau, por exemplo, considera a contagem do número de nós adjacentes a ele (Wasserman & Faust, 1994), a de Autovetor pondera as conexões diretas e indiretas que chegam a um nó (Bonacich, 1987, 2007; Ramos, Lopes, & Araújo, 2017; Wasserman, 1994). Ou seja, a Centralidade de Autovetor pondera os pesos atribuídos não somente às ligações diretas entre unidades de análise, mas também as ligações indiretas, considerando interações de *n*-ordem (Bonacich, 2007; Bonacich & Lloyd, 2001). Neste sentido, esta medida torna-se uma poderosa ferramenta para o desporto, pois pode realçar o papel relativo de cada nó dentro do sistema de jogo, após ter pesado todas as suas ligações, sejam diretas ou indiretas (Afonso, Laporta, & Mesquita, 2017; Hurst, Loureiro, Valongo, Laporta, Nikolaidis, & Afonso, 2017; Hurst, Loureiro, Valongo, Laporta, Nikolaidis, & Afonso, 2016; Loureiro, Hurst, Valongo, Nikolaidis, Laporta, & Afonso, 2017).

3. SINOPSE DE INVESTIGAÇÃO CENTRADA NA ANÁLISE DE REDES SOCIAIS EM JOGOS DESPORTIVOS

Jogadores como unidade de análise e métricas usuais

A investigação com recurso à ARS em Ciências do Desporto tem ocorrido, precisamente, maioritariamente no âmbito da AJ. Neste contexto, as pesquisas têm recorrido, de forma quase exclusiva, aos jogadores como unidade de análise (os nós da ARS) e aos passes como ligações entre essas unidades (as arestas da ARS).

No futebol, alguns autores, considerando jogadores como nós e o passe entre eles como arestas, revelaram padrões na construção ofensiva. Malta & Travassos (2014), através das Centralidades de intermediação, Grau (entrada e saída), revelou que a equipe analisada (pertencente a Primeira Liga Portuguesa) possuía padrões preferenciais de transição defesa-ataque, onde as decisões do tipo de passe utilizado dependiam do número de participantes que cercavam a bola. Alves, Gonçalo, José, Vasco, & Miguel (2018) analisaram uma seleção de futebol (sub-20), onde os jogadores médio-centro e defesa-esquerdo fora, através da Centralidade de Grau foram os atletas mais centrais da rede, enquanto que o médio-centro, através da Centralidade de Autovetor, foi o Jogadores-Chave na dinâmica coletiva ofensiva da equipa até o golo. Na mesma linha Gama, Passos, Davids, Relvas, Ribeiro, Vaz, & Dias (2014), observaram seis jogos da Primeira Liga Portuguesa de Futebol e revelaram que alguns jogadores foram peças-chave na construção do ataque assumindo um papel de elevada centralidade e importância na dinâmica da equipe.

Apesar da maioria dos estudos terem sido aplicados no futebol, a ARS já foi utilizada em outros JD, como o basquetebol. Clemente, Martins, Kalamaras, & Mendes (2015) verificaram a contribuição individual dos jogadores das diferentes posições táticas no processo de ataque em equipas de diferentes níveis de competição (sub-14, sub-16, sub-18 e amadores com mais de 20 anos). Apesar de não encontrarem diferenças entre as posições táticas nos diferentes níveis competitivos, a principal diferença foi entre a Centralidade de Grau de Entrada e Saída, onde o armador, em particular, obteve um papel de destaque e de ligação entre os demais jogadores recebendo e passando a bola na construção ofensiva. No cricket por Dey, Ganguly, & Roy (2017) objetivaram formarem uma equipa internacional de pertencentes a Liga Principal Indiana de 2016. As centralidades de Intermediação, Proximidade e Grau indicaram que 11 jogadores tiveram melhor desempenho e mereciam pertencer a equipa. Porém, os autores revelaram que outros aspetos merecem atenção, como: atuação contra um oponente forte, o desempenho e companheirismo com um membro efetivo de equipe, entre outros.

No Voleibol, um dos primeiros estudos realizado foi o de Clemente, Martins, & Mendes (2015) que verificaram a variação de Centralidade de Grau (entrada e saída) e *PageRank* entre as redes de duas equipes de diferentes níveis (com idade abaixo de 12 anos e amadores) do Campeonato Regional Português de voleibol. Apesar de não possuir diferenças significativas entre os dois níveis analisados, os jogadores de maior e menor nível de proeminência foram da Zona 3 e 5 respetivamente, pois o primeiro deve-se ao fato que nas duas equipes analisadas o primeiro toque era sempre direcionado para o jogador desta zona na fase de ataque, enquanto que no segundo esta zona foi associada a menor eficácia de ataque.

Um outro estudo em futebol apresentou já alguma inovação relativamente às métricas, embora não relativamente à unidade de análise. Aquino, Carling, Vieira, Martins, Jabor, Machado, Santiago, Garganta, & Puggina (2018) analisaram 18 partidas da 3ª divisão do futebol brasileiro, através do efeito de variáveis situacionais (i.e. estágio da competição, localização da partida, qualidade de oposição e resultado do jogo), formação de equipe adversária, desempenho de corrida a partir das posições de jogo (GPS), e ainda, a interação da equipe utilizando a ARS. Dentre os principais resultados, os jogadores meio-campistas centrais/externos se encontravam mais próximos de outros companheiros (maior Centralidade de Proximidade), "controlavam" mais redes (elevada Centralidade de Intermediação), realizava mais passes (Grau de Saída) e foi um jogador-chave na organização ofensiva da equipa (maior centralidade de Autovetor) em comparação com os defensores centrais, externos e os atacantes. Aqui, temos o primeiro vislumbre de ponderação de ligações indiretas, com utilização do Autovetor, mas ainda de forma tímida.

Também no Râguebi, Sasaki, Yamamoto, Miyao, Katsuta, & Kono (2017) revelaram os *turnovers* realizados durante as ações defensivas na Copa do

Mundo de Râguebi 2015, através da centralidade de Autovetor, revelando que um maior desempenho na rotatividade da defesa contribuiu para a vitória. Em suma, as pesquisas utilizando ARS no desporto vêm utilizando quase exclusivamente os jogadores enquanto unidades de análise o que, sendo positivo, apenas providencia um quadro incompleto do fenómeno complexo que é a performance e, ademais, não utiliza todas as potencialidades oferecidas pela ARS.

Ações de jogo como unidade de análise e ponderação de ligações indiretas

Mais recentemente, as pesquisas vêm adotando um paradigma diferenciado, expandindo as potencialidades da ARS no desporto, nomeadamente: (i) adotando as ações de jogo como unidades de análise; e (ii) recorrendo à Centralidade de Autovetor como forma de ponderar as ligações diretas e indiretas entre unidades de análise (e.g. Hurst, Loureiro, Valongo, Laporta, Nikolaidis, & Afonso (2017); Hurst, Loureiro, Valongo, Laporta, Nikolaidis, & Afonso (2016); Loureiro, Hurst, Valongo, Nikolaidis, Laporta, & Afonso (2017). Estes estudos foram todos realizados em voleibol de alto nível. Hurst, Loureiro, Valongo, Laporta, Nikolaidis, & Afonso (2017); Hurst, Loureiro, Valongo, Laporta, Nikolaidis, & Afonso (2016), analisaram o Serviço (K0), Side-out (KI), contra-ataque (KII) e Contra-ataque do Contra-ataque (KIII) no primeiro estudo e a Cobertura de Ataque (KIV) e Bola Morta (KV) no segundo, na fase de grupos do Women's World Grand Prix 2015. Os resultados indicaram que jogar fora do sistema (*off-system*) foi central nos Complexos analisados, principalmente em ações como: Condições de Distribuição, Zona e Tempo de Ataque. Para além disso, e apesar do KV liberar um número maior de jogadores tornando a ação de ataque potencialmente vantajosa, o jogo mostrou-se mais lento (com tempo de ataque mais lentos) mesmo com melhores condições de distribuição.

Afonso, Laporta, & Mesquita (2017) averiguaram as diferenças entre o KII e KIII no voleibol feminino analisando a fase final do Grand Prix 2015. Tratar estes dois complexos da mesma forma pode fazer com que informações sejam perdidas ou tratadas de forma similar quando apresentam diferenças, como por exemplo: melhores Condições de Distribuição, jogo mais lento (Tempo de Ataque 3) e menos Zonas de Ataque (4 e 2) no KIII, enquanto no KII há uma maior variabilidade das zonas de ataque (zonas 4, 2, 1 e 6 mais centrais).

Seguindo a lógica anterior, Loureiro, Hurst, Valongo, Nikolaidis, Laporta, & Afonso (2017) analisaram os Complexos 0, I, II e III no voleibol masculino de alto nível (Copa do Mundo Masculina 2015) e contrariamente ao voleibol feminino, os resultados indicaram que no KI as equipes jogaram em condições próximas das ideais (*in-system*), porém apresentou reduzida variação em relação às zonas e tempos de ataque, já no KII em piores condições que no KIII, que, apesar existir maior variabilidade do número de bloqueadores (triplo e duplo) e melhores Condições de Distribuição, o tempo de ataque foi lento, provavelmente pela necessidade de recuperação do bloqueio, dificultando assim a participação em ataque mais rápidos.

Em suma, estes estudos revelaram a pertinência e aplicabilidade de considerar unidades de análise não-agenciais como, por exemplo, as ações de jogo. Ademais, estes estudos buscaram uma abordagem sistémica do jogo (McGarry, Anderson, Wallace, Hughes, & Franks,, 2002), procurando avaliar as diferentes fases do jogo e suas interações diretas e indiretas (Hurst, Loureiro, Valongo, Laporta, Nikolaidis, & Afonso, 2017; Hurst, Loureiro, Valongo, Laporta, Nikolaidis, & Afonso, 2016; Loureiro, Hurst, Valongo, Nikolaidis, Laporta, & Afonso, 2017.

4. LIMITAÇÕES E POSSIBILIDADES DE FUTUROS ESTUDOS

A AJ constitui uma poderosa abordagem à análise da performance. Neste contexto, a ARS vem emergindo como uma metodologia de análise com elevado potencial. No entanto, as pesquisas neste âmbito estão grandemente limitadas à utilização de unidades de análise agenciais (p.e., jogadores), dessa forma ficando por explorar unidades não-agenciais (p.e., ações de jogo), que conferem informação diferenciada relativamente aos padrões de jogo. A utilização de unidades não-agenciais é possível devido às raízes matemáticas da ARS (i.e., Teoria dos Grafos). Recentemente, esta questão vem sendo explorada por investigações em voleibol de alto nível (Hurst, Loureiro, Valongo, Laporta, Nikolaidis, & Afonso, 2017; Hurst, Loureiro, Valongo, Laporta, Nikolaidis, &

Afonso, 2016; Loureiro, Hurst, Valongo, Nikolaidis, Laporta, & Afonso, 2017, mas desconhecemos aplicações similares noutras modalidades.

Realce, ainda, para o facto de poucos estudos recorrerem à Centralidade de Autovetor que, contudo, apresenta um elevado potencial por pesar as ligações indiretas e não somente as diretas e, assim, efetuar cálculos ponderados que consideram um maior nível de complexidade e, porventura, aportam uma perspetiva mais profunda acerca dos fenómenos estudados. As recentes pesquisas em voleibol (Hurst, Loureiro, Valongo, Laporta, Nikolaidis, & Afonso, 2017; Hurst, Loureiro, Valongo, Laporta, Nikolaidis, & Afonso, 2016; Loureiro, Hurst, Valongo, Nikolaidis, Laporta, & Afonso, 2017) adotaram ações de jogo enquanto unidades de análise e o Autovetor para pesagem de ligações indiretas. Contudo, não estudaram o jogo na sua globalidade, mas somente alguns dos seus complexos, carecendo, desta forma, de uma verdadeira visão sistémica.

Adicionalmente, não deixa de ser surpreendente que, sendo a ARS utilizada pela AJ como forma de analisar a performance, não haja, do nosso conhecimento, estudos que relacionem as ações de jogo com a eficácia das jogadas. Embora esta constitua uma prática comum na AJ, quando recorre às mais diversas metodologias, tal abordagem ainda não foi concretizada neste contexto. Finalmente, muitos estudos, nas diferentes modalidades, situam-se no sexo masculino. Todavia, é reconhecido que, em muitos desportos, a performance é qualitativamente distinta, o que justificaria a necessidade de se estudarem os mesmos fenómenos nos dois sexos. Caso contrário, existe o risco de os resultados obtidos no masculino serem indevidamente extrapolados para o feminino.

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III. Estudos Empíricos

3.1 Interaction network analysis of the six game complexes in high-level volleyball through the use of Eigenvector Centrality

PLOS ONE

RESEARCH ARTICLE

Interaction network analysis of the six game complexes in high-level volleyball through the use of Eigenvector Centrality

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Abstract

Social Network Analysis establishes a network system and provides information about the relationships (edges) between system components (nodes). Although nodes usually correspond to actors within the network (e.g., the players), it is possible to stipulate *game actions* as nodes, thus creating a network of the flow of game actions. In this study, Eigenvector Centrality (a form of weighted centrality that considers *n*-order connections) was used to identify differences in the centrality of distinct game actions within each of the six game complexes of volleyball. Thirteen matches (46 sets, 2,049 rallies) of the final round of the 2015 FIVB's World Grand Prix (Women) were analyzed. Results showed that analyzing actions as actors (i.e., nodes) offers a clear and comprehensive understanding of game flow and poses an interesting alternative to mainstream research where players are considered nodes. Functional differences between the six game complexes were highlighted, denoting the validity of such division. Out-of-system playing (i.e., having to set the attack under non- ideal conditions, e.g., in KI, KII, KIII and KIV), emerged as a regularity of the game and should be translated into the training process.

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Introduction

The need for a systemic analysis of performance has been proposed extensively (e.g., [1–3]). In this vein, performance analysis (PA) is conducted to establish an ecological view via the under- standing of the relationships between variables within a system [1]. Systemic approaches to PA treat systems as wholes, albeit composed of interacting independent parts [2], and as entities capable of self-organizing to produce non-linear patterns. Team sports (TS) fall into this con- ceptual framework because they are characterized by interconnected systems that change their state over time through self-organization properties [3]. It can be difficult to access the inher- ent complexity of systems, although some promising methods have emerged to address this issue.

Among such methods, Graph Theory (GT) provides a useful topological analysis of a com- plex system that offers quantitative insights into systemic behavior [4], which may then be interpreted qualitatively. Mathematical GT has been the key to generating advanced quantita- tive methods for Social Network Analysis (SNA) [5]. Making use of methods derived from GT and sociometry, SNA offers a systemic view of the game [6, 7] and establishes a global network of the system through the study of interconnections (edges) among sets of actors (nodes) [8]. As such, SNA highlights the structural relationship between actors and reveals global network features, as well as individual network positions and subgroups within a whole network, which are the most important information transmitters [9]. Among others, centrality–which reveals the network position of individual actors or elements–is a key concept of SNA (see e.g. [10]).

Although SNA has existed for some time [11, 12], it has only been applied to sport relatively recently, which is evident in the systematic review published by Wäsche and colleagues [13].
From this work, Wäsche and colleagues proposed a six-dimension conceptual typology of SNA application that offers a renewed understanding and systematization of this new field research field. While two of these dimensions (i.e., competition networks and interaction net- works) are specific to the sport, the other four (i.e. inter-organizational network, intra-organi- zational networks, affiliation networks, and social environments) are related to other social contexts. Competition networks (inter-event) examine sport outcomes and results by the iden- tification of structural patterns and relative performances of athletes or sports teams. Interac- tion networks, on the other hand, focus on the interactions between players within a team, thus highlighting the relationships between game actions and how such interconnectivity can influence effectiveness.

As showed by Wäsche et al. [13], competition networks are much more widely studied than interaction networks, which reinforces the value of researchers exploring the latter. Here, the focus of research has been on the interactions between players (nodes) in different game phases through their passes (edges). For example, Gama et al. [6] examined attack patterns in soccer via the individual actions of key players and their influence on team performance in the Portuguese Football Premier League; their personalized metric was similar to degree centrality. Clemente et al. [14] assessed the intra-team tactical behavior in basketball attack organization using distinct centrality metrics of network (degree prestige, degree centrality). Duch et al. [15] analyzed the performance of individual players, and of teams, in the 2008 European Cup soccer tournament and concluded that flow centrality provides a powerful objective quantifi- cation of individual and team performance.

Such contributions have provided useful insights, but interaction networks such merit a broader body of research that incorporates the relational perspective proposed by Emirbayer [16] and Elster [17]. Additionally, SNA also offers the possibility of defining action variables as nodes [18, 19], and their relationships as edges. This perspective brings a departure from most current research and provides different avenues for understanding game flow. This action- centered approach (as opposed to a player-centered approach) might constitute a more suit- able pathway towards an understanding of the functional specificities of each game phase (in volleyball, the technical term is game complex), and thereby paving the way to better pedagogi- cal models for teaching the game and training models that are more coherent with the demands of the game [19].

The centrality of a variable is usually determined by the absolute number of its direct con- nections (e.g., Degree Centrality [10]), which might provide an analysis that neglects indirect connections. Eigenvector Centrality, in comparison, weights the indirect connections in addi- tion to direct connections (e.g., second- or third-order links between nodes) [10, 20], and therefore provides a more complete overview of the role of each node within a systemic per- spective. Until now, centrality measures such as Eigenvector Centrality have mainly been adopted by sociometric approaches and quantitative network studies of ethnography [5, 21]. However, to our knowledge, this metric is still underused in performance analysis of sports [19, 22, 23]. One exception is a study by Sasaki et al. [24], which used Network Centrality Anal- ysis (Density and Eigenvector) to determine the tactical leader of high-level rugby teams (2015 Rugby World Cup) and to analyze the impact of defensive actions on the outcome of the game. This revealed the existence of decisive relational structures where the highest turnover performance would contribute to the winning game, and that certain individuals play key roles in the game (e.g., "fly-half"). Because game events are likely to produce direct as well as indirect consequences, the application of Eigenvector Centrality in high-performance sport settings needs to be further explored [25].

Volleyball is a team sport composed of six functionally distinct but interconnected game complexes (Ks). The six game complexes are as follows (based on [18, 19, 26]): Complex 0 (K0) or serve; Complex I (KI) or side-out; Complex II (KII) or side-out transition; Complex III (KIII) or transition of transition; Complex IV (KIV) or attack coverage; and Complex V (KV) or Freeball and Downball. Despite the rationale behind the theoretical compartmentali- zation of volleyball into six functionally distinct game complexes, research has focused mainly on KI and KII (e.g. [27, 28]), usually incorporating K0, KIII, KIV and KV into KII. This com- bining of complexes has produced results that might be misleading because important inter- complex differences are likely to be averaged out. Although a number of investigations have focused on the characteristics of subsets of the six game complexes [29, 30], analyzing the
game without considering all the complexes may limit the ability to acquire an in-depth under- standing of the game [30]. Here, we propose to address this issue in women's volleyball, a deci- sion made because women's volleyball is less well studied than men's volleyball [31].

The application of SNA to volleyball is still in a preliminary phase, and Eigenvector Central- ity has seldom been applied. Indeed, to date just three studies have utilized Eigenvector Cen- trality [18, 19, 23]. These studies have investigated complexes I, II and III in the group stage of the women's 2015 World Grand Prix [23] and the men's 2015 World Cup [22], and also com- plexes IV and V in the group stage of the women's 2015 World Grand Prix [19]. More research is, however, required to fully explore the contributions of Eigenvector Centrality in sports.
This is particularly true for women's volleyball because it is less well studied than men's volley- ball [31]. Moreover, studies on interaction networks have not used Eigenvector Centrality [7, 15, 32, 33], and thus an opportunity exists for this to be explored.

Our aim, therefore, was to examine the functional differences between the six game com- plexes in high-level women's volleyball from the perspective of SNA, and specifically using the insights offered by Eigenvector Centrality. Here, we will use an action-centered approach and consider game actions as nodes to establish an interaction network [13]. We assessed all six game complexes because we expected each to have different characteristics and weights for each variable, particularly setting conditions. More specifically, we anticipated that the weights for the most critical game actions (i.e., Setting Conditions, as they represent the link between the first and final contact with the ball) would be different for each complex, albeit with a pre- dominance of Setting Condition C (i.e. poor conditions for setting the attack). We also hypoth- esized that the patterns for each complex would depend on the interconnectivity with previous complexes. Here, we specifically anticipated that block opposition would be enhanced (i.e., more blockers opposing the attack) when playing in KII and KIII, and impaired when playing in KIV and KV.

Material and methods

Sample

Thirteen matches of the final round of the 2015 FIVB World Grand Prix (one of the main world volleyball competitions for women) between the national teams of Brazil (4 matches), China (5 matches), Japan (4 matches), Italy (4 matches), Russia (4 matches) and the USA (5 matches) were observed. Thus, a balanced number of matches for each team was observed. We analyzed a total of 46 sets (8 three-set matches, 3 four-set matches, and 2 five-set matches), which corresponds to 2,000 plays or rallies, including 2,017 ball possessions related to K0, 1,800 to KI, 1,423 to KII, 1,204 to KIII, 258 to KIV, and 273 to KV. This resulted in the production of a network with 125 nodes and 1,865 edges. The Ethics Committee at the Centre of Research, Education, Innovation and Intervention in Sport, University of Porto, provided institutional approval for this study (CEFADE 16.2017).

Measures

The game of volleyball can be divided in phases or subsystems, usually termed *game complexes* in the specialized literature [26]. Each game complex displays distinctive features and sequences of occurrence. Six *Game Complexes* (K's) were considered and are synthesized in Fig 1: Complex 0 (K0) or serve; Complex I (KI) or side-out; Complex II (KII) or side-out transition; Complex III (KIII) or transition of transition; Complex IV (KIV) or attack coverage; and Complex V (KV) or Freeball and Downball (based on [18, 19, 26]).

The *Initial Position of the Server* was based on Quiroga et al. [34]: Zones 1, 6 or 5; see Fig 2A. *Serve Type* was adapted from Costa et al. [31] Quiroga et al. [34]: float jump serve (i.e., without ball rotation); jump serve (i.e., with ball rotation); and standing serve (i.e., without jumping and including both the float and topspin standing serves; their reduced occurrence in high-level volleyball justifies their grouping into a single category).

The *Zone of First Contact* can occur in the form of reception or defense and was stipulated following the six official zones according to the FIVB rules (see Fig 2B). In the case of defense, we added the 'Others' (OT) zone. This corresponds to the area where the athlete can retrieve balls outside the bounds of the court after having touched the block. In serve-reception, this category is not required, as a previous contact with the block is not possible.

Setting Conditions were adapted from Marcelino et al. [28], Laporta et al. [30], Afonso and Mesquita [35], and refer to the attack options available to a setter before setting the attack: A—the setter has all the attack options available, and therefore the ideal setting conditions; B–the

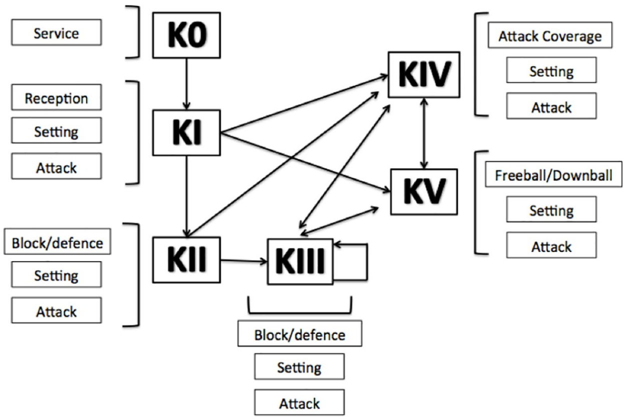

Fig 1. The six game complexes in volleyball.

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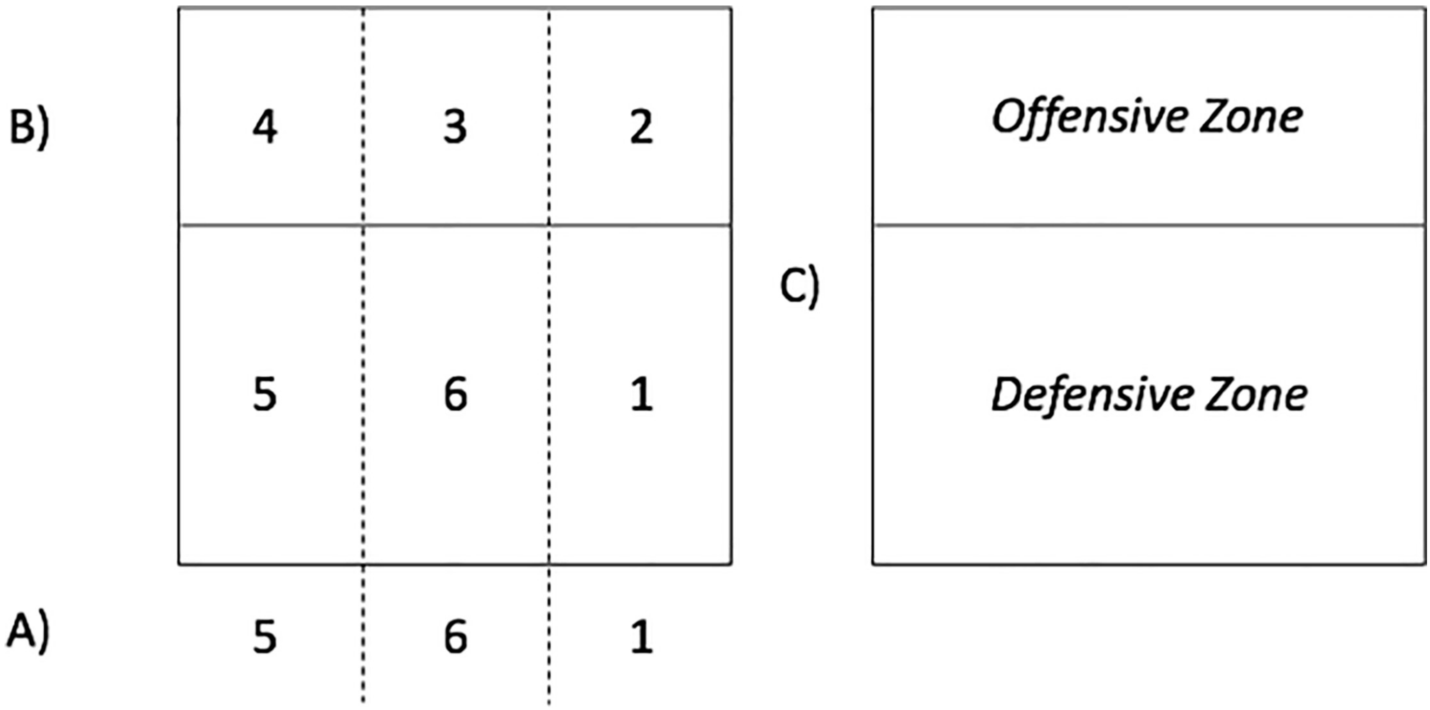

Fig 2. Variables illustration of initial position of server, First Contact, Attack Zone and Target Zone in KV. (A) Initial Position of the server; (B) First contact and Attack Zone; and (C) Target Zone in KV.

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setter can deploy quick attacks, but some attack options are not possible (e.g., crossing of players); C–the setter can only use high sets, and thus it is considered as out-of-system playing.

The *Attack Zone* made use of the six official zones determined by FIVB rules (see the Fig 2A). Attack Tempo was simplified from Afonso and Mesquita [36] and Costa et al. [31], and refers to the synchronization between the setter and the attacker: a) in tempo 1 the attacker jumps before or at the same time as the set; b) in tempo 2 the attacker performs two steps after the set; and c) in tempo 3 the attacker waits for the ball to ascend and then performs a three- or more-steps approach.

Block Opposition was adapted from Afonso and Mesquita [35], and considered the following categories: no-block (B0); single or individual block (B1); double block (B2); and triple block (B3). The *Number of Available Players Before Attack Coverage* was adapted from Laporta et al. [30], Laporta et al. [37] and refers to the players that were available to attack before an attack coverage occurring. The *Number of Coverage Lines* consists of imaginary curved lines (progressing from the net to the endline) established by the players that were in the defense position in the moment of the attack.

Freeball represents the team organization for a ball that will have to be returned softly by the opponent due to poor conditions for performing the third contact [38]; *Downball* occurs when it is unfavorable for a player to attack, but they still perform a standing spike [39]. The *Target Zone in KV* (see Fig 2C) is the area of the court in which the ball was dropped. It can be categorized as an offensive or defensive zone according to official FIVB rules (i.e., from the 3-meter line until the net or behind the 3-meter line). The analyzed variables are summarized in S1 Table.

Data collection

The matches were viewed using the websites *laola.tv* and *youtube.com*. All matches were available in high-definition (1080p) and recorded with a moving lateral view of the court (i.e., broadly aligned with the net and with a moving angle), which was suitable for the variables we intended to observe in this investigation. Indeed, the variables were selected considering these specifications. Likewise, we chose specific instruments to analyze our variables of interest considering the characteristics of the video footage.

Data worksheet

The data were input into an analysis worksheet created with Microsoft[1] Excel[1] 2017 (Microsoft Office Professional 365 Version 15.30, E.U.A.) using the macro function to instantly catalogue the required codes in the appropriate cells.

Training protocol for the observers

For the observer's training protocol we expanded upon the methodological concerns outlined by Araújo et al. [40]. Three observers, each with a master's degree in the area of volleyball training and with extensive experience as a volleyball coach (i.e., more than five years as coaches and with victories in national championships in their résumé), were trained to use the instrument for a period of three months. Two reliability tests were performed in this period (the first after two months of testing the instrument, another three months after) to ensure consistency and to allow for any necessary adjustments to the variables and categories of the final instrument. Over the three months of training, weekly meetings were held for instrument explanations and clarifications, discussion of emerging problems, and a joint analysis of different matches (not used in the current investigation) [41].

As the analysis is designed to apply to both women and men's volleyball, the first reliability testing comprised an analysis of 217 actions from a high-level men's match (final match to qualify for the 2015 FIVB Volleyball World League Pool E, totaling 5 sets). Four of the 13 variables obtained Kappa values below 0.75. This led to an in-depth discussion about these variables and their categories, which we then redefined and improved to increase clarity and the likelihood of more homogeneous recordings.

After further training meetings (analyzing both men's and women's matches), a second reliability test of the instrument was performed, this time using a high-level women's match (play-off match of 2014/2015 Turkish Women's Volleyball League, totaling 5 sets), and a total of 209 actions. This match was from a different competition to that considered in our study) in order to avoid bias when moving towards analysis of the target competition. While reliability improved, one variable (Type of Reception Line) still presented values below the expected 0.75. Therefore, after critical discussions, the researchers decided to remove this variable from the study. The final analysis worksheet thus included the 11 variables described in S1 Table.

We conducted the final assessment of data reliability measurement with 415 actions from two high-level matches (final phase of the 2015 World League and 2015 World Grand Prix, totaling 10 sets). All variables presented Cohen's Kappa values above 0.75, as suggested in the literature [42].

Data analysis

After being inserted, data were examined using SPSS[1] for Mac (Version 24, IBM[1], E.U.A.). A descriptive analysis was conducted to ensure data quality (verify input errors, data frequencyand others). A calculation of Eigenvector Centrality was then performed using Gephi 0.9.1 for Mac (MacRoman, France). Nodes were placed at the periphery of the network so that all inter- actions could be clearly visualized.

The contrast of node size and color were perfected to reflect the magnitude of their Eigenvector values. Node size was manipulated using the intrinsic units provided by the software, which were specified between 300 (minimum) to 1,500 (maximum). These values are a measure of arbitrary, relative units, where the value (node size) determines the degree of visual contrast between variables according to the different Eigenvector values.

Edges were also depicted with a variable thickness in order to better reflect Eigenvector values. Although nodes reflect the weight of both direct and indirect connections, edges provide a measure of direct connections only. Therefore, thicker edges correspond to a greater number of connections between two nodes. Edges are defined in units, i.e., number of connections. A direct connection between two variables is established if they are simultaneous or consecutive. For example, Attack Tempo occurs simultaneously with Attack Zone, so some category of Attack Tempo will always connect to some category of Attack Zone. Also, Attack Tempo is preceded by Setting Conditions and followed by Block Opposition. Therefore, it also establishes direct connections with these two variables. However, there are no direct connections between Attack Tempo and Zone of First Contact, as they do not follow consecutively. Nonetheless, Eigenvector Centrality calculates the weight of indirect connections, such as the following: Zone of First Contact–Setting Conditions–Attack Tempo.

Data reliability

After data collection was completed, inter-observer reliability was assessed with 10% of the total sample (a total of 210 randomly chosen actions) as suggested in the literature [42]. A calculation of Cohen's Kappa provided values ranging between 0.80 and 1, which are above the threshold of 0.75 proposed by Tabachnick and Fidell [43]. Intra-observer reliability analysis was conducted with the same 210 actions approximately two months after the first observations. All variables achieved values of Cohen's Kappa between 0.791 and 1, again surpassing the minimum accepted threshold of 0.75.

Results

A global network of within-complex and between-complex interactions was established (Fig 3) using Eigenvector Centrality to provide a map of interactions.

A visual inspection of the network revealed the existence of functional distinctions between game complexes. Quantitative values of Eigenvector Centrality for each game complex are exhibited in S2–S7 Tables.

Eigenvector values for the variables belonging to Complex I are presented in S3 Table, highlighting the high values for Setting Condition C, Attack Zones 2 and 4 and Attack Tempo 2 and 3.

S4 Table presents the variables belonging to Complex I. Note the high centrality values for Setting Condition C, Attack Zone 4, Attack Tempo 2 and 3, and Single and Double-block.

Eigenvector values for the KIII variables are shown in S5 Table. Setting Condition C and Attack Tempo 2 presented high values in their categories. In KI, the zones with higher Eigenvector values were Zone 1 and 5, followed by Zone 6, whereas in KII, Zones 5, 1 and 6 showed the highest values. The same regularity was observed in KIII.

Block Opposition had similar values for KII and KIII, with Double Block presenting the highest values, followed by Single Block. In KIII the Triple Block obtained an Eigenvector value superior to that of KII.

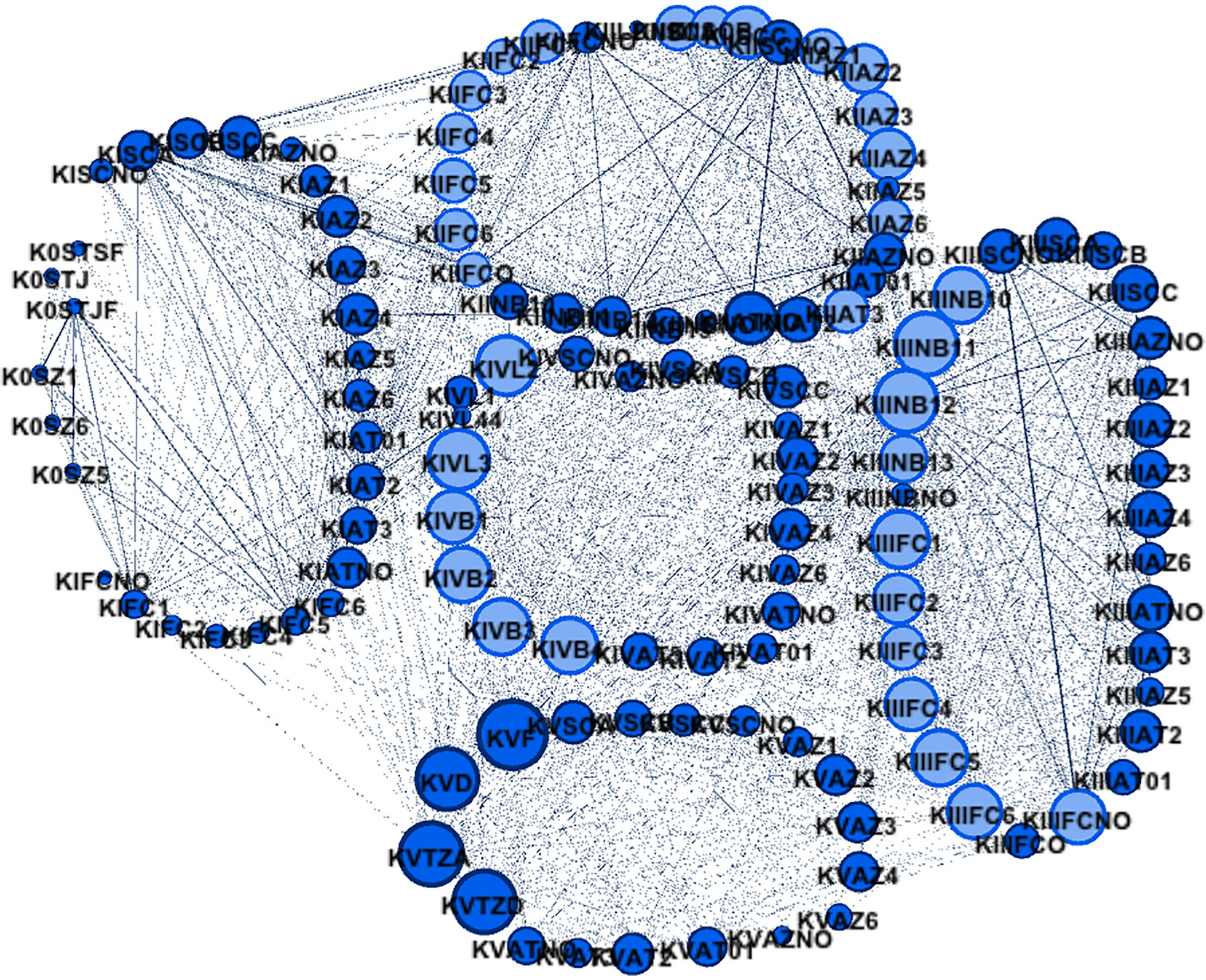

Fig 3. Network with Eigenvector Centrality for all complexes. Terminology: in each node, codes are represented by the name of complex (e.g., KII), followed by the variable and its category (e.g., KVFCZ6 indicates that the action occurred in complex V, the variable in question was Zone of First Contact, and the category is Zone 6). Codes for the different variables: IPS–Initial Position of the Serve; ST–Serve Type (Jump, Jump-Float and Standing-Float); FC–Zone of First Contact; SC Setting Condition; AZ–Attack Zone; AT–Attack Tempo; BO–Block Opposition; KIVB–Number of Available Player Before of Attack Coverage; KIVL–Number of Coverage Lines; KVD and KVF–Downball and Freeball; KVTZ–Target Zone in KV (Attack or Defense Zone).

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The Eigenvector values of the variables belonging to Complex IV are presented in S6 Table: note the high values for Setting Condition C, Attack Zones 2 and 4 and Attack Tempo 2 and 3.

S7 Table shows the Eigenvector values of the complex V variables, where Setting Conditions A, Attack Tempo 1 and 2 revealed a higher value of centrality. For Setting Conditions, KI exhibited the highest Eigenvector value for Setting Condition C, followed by Setting Conditions A and B. In KII, Setting Condition C also had a higher centrality value, with lower values for Setting Conditions A and B. KIII followed the same trend of Setting Condition C having the highest value, although Setting Condition A had a larger value than Setting Condition B. KIV was defined by higher values of Eigenvector Centrality compared to the other complexes, and in it Setting Condition C had the highest Eigenvector value, well above the values for Setting Conditions A and B. Finally, KV was the only game complex where Setting Condition A had the highest value, followed by Setting Conditions B. For this complex, Setting Condition C had the lowest centrality value.

In KI, the Attack Zones with the greatest Eigenvector centrality were Zones 2, 4 and Zone 3. In KII, Zones 2 and 4 had the highest centrality values, followed by Zone 1. Attack Zone 4 was the most central in Complex III, followed by Zones 2 and 3. In KIV, Zone 2 and 4 presented the highest values, while the centrality of other Attack Zones fell below 0.3. In KV, in addition to Zones 2 and 4, Zone 3 also presented a high Eigenvector value.

The variable Attack Tempo had similar values for all categories in KI, although Attack Tempos 2 and 3 had the highest Eigenvector values, followed by Attack Tempo 1. In KII, Attack Tempos 2 and 3 had the highest Eigenvector values. In KIII, Tempo 2 presented the highest value, followed by Tempos 3 and 1. In KIV Tempo 2 had the highest value, followed by Tempo 3. In KV, the most central categories were Tempos 2 and 1, with Tempo 3 exhibiting the lowest value of this complex.

Discussion

The aim of the present study was to conduct a systemic analysis of high-level women's volleyball, with special consideration of the game actions comprising its six interconnected game complexes. Our rationale for this was based on the six-dimension conceptual typology of Social Network Analysis (SNA) applied to sport Wäsche et al. [13], which establishes an interaction network to examine the degree of interconnectivity and specificity of the different game complexes. In order to establish the quantitative and topological relationships between game variables across the six complexes we used SNA and Eigenvector Centrality. This metric provides the opportunity to access not only the direct connections between game actions, but also the indirect connections within each complex and between complexes. Another novel aspect of this research was the analysis of game actions as nodes, while previous research has applied player-centered approaches.

Preferential attachments [7] from indirect and direct connections were identified, and these highlight features of the game dynamics within each complex and between complexes. The identification of such preferential attachments within a small-world network from an interaction network (intra-event) creates the possibility for identifying the critical game actions that impact more on the game flow, and therefore on the performance. Moreover, this paper answered the call by Passos et al. [7] for more research that measures the temporal and spatial distribution of high frequency nodes pertaining to interactions in team sports. Here, we have accomplished this with a relevant sample of 2,017 ball possessions in a total of 46 sets, with 125 nodes and 1865 edges.

We hypothesized that some game actions would have different weights in distinct game complexes, and would thus have varied impacts on game flow, i.e. on the patterns and configurations of the game dynamics. By using Eigenvector Centrality it was evident that there were *preferential attachments* [7] that explicitly impacted on the game dynamics. For instance, playing out-of-system (strongly related to Setting Conditions, Attack Tempo and Zone) emerged as a central game pattern in several complexes. Setting the attack under non-ideal conditions (i.e. Setting Condition C) had a central role in almost all complexes (I, II, III and IV). This suggests that in four of five game complexes (as K0 is an enclosed complex with only one action, i.e., the serve), setting out-of-system is more central than setting in-system (A), or marginally out-of-system (B), conditions. Although setting in-system is considered crucial for creating the best options for attack tempo and attack zone [44], our data emphasized that the use of non-ideal, out-of-system setting conditions is a regularity in high-level women's volleyball. These findings are somewhat different to those of previous research using Eigenvector centrality in women's volleyball. Hurst et al.[23] analyzed the first phase of the 2015 World Grand Prix and showed that setting conditions had roughly equivalent centrality values in complexes I and III, while setting out-of-system was only predominant in KII. Our study was applied to the final round of the 2015 World Grand Prix, which is likely to have more balanced matches because the team levels are highly equalized (after all, only the best of the best classify for this stage). These differences in findings might, therefore, depend on the competition stage, although more research is necessary to verify if this trend is consistent in other samples.

In this study, Eigenvector Centrality was shown to be a powerful tool for establishing the interconnectivity between game actions and their relative roles in each game complex (Setting Conditions, for example, establish the possibility for linking the first contact with the third contact in a functional manner). This requires a consideration of the interplay between all the game actions (i.e., the whole network), hence highlighting the clear advantage of adopting the SNA approach and Eigenvector metric. Similarly, we observed higher centrality values for slower attack tempos, and attacks at the extremities of the net, and it is possible that these are derived from the predominant out-of-system setting conditions. Although prior studies already devoted some attention to Setting Conditions (e.g., [45, 46], [47]), none considered the interactions among all the different game actions, i.e. there was no weighting of indirect connections. Such studies have also tended to analyze each condition was studied in a somewhat rigid manner, such as by considering specific zones of the court, instead of adopting a more flexible and functional analysis. They therefore do not correspond well to the reality and complexity of high-level games.

We anticipated that the interconnectivity with previous complexes would influence the patterns of following game complexes: block opposition, for instance, would be enhanced in KII and KII (i.e., more blockers opposing the attack in more unpredictable complexes) and impaired conditions in complexes with less uncertainty (i.e., KIV and KV). Our use of Eigenvector Centrality allowed us to identify some specificities of the game complexes, and the relationships each complex had with subsequent complexes. KII, for example, exhibited a greater unpredictability because it had consistent centrality values across the different attack zones and tempos. Such uncertain conditions then made it possible for KIII to be more predictable, evident by Attack Tempo 2 having a higher Eigenvector value than the Attack Tempos 1 and 3. In KV, there was greater Eigenvector Centrality for faster attack tempos (i.e., Tempos 2 and 1), coupled with a more even distribution of front row attack zones (i.e., Zones 2, 3 and 4). This implies that faster attack tempos favor the unbalancing of the block [35], which is supported in our study by higher centrality values for single and double blocks in KIII. The strong relationships between complexes and their subsequent game complexes are apparent, and this appeals to the utilization of methodologies that consider the interconnectivity between game actions and complexes, as is considered in the SNA approach.

Overall, the present study demonstrates the power of SNA in accessing the game ecology (i.e., in considering its dynamics and complexity) and for allowing the identification of game patterns that are context-dependent. Quantifying events in team sports while accounting for their interconnectivity is far from trivial. Moreover, the relevance of adopting an *action-centered approach*, as carried out in this study, is that it (a) provides a powerful and objective quantification of all actions considering both its direct and indirect linkages, and (b) delivers a deeper comprehension of the specificity and interconnectivity of game actions considering the game phases where they take place. In light of the shortcomings of previous studies on interaction networks, we believe the current research adds to the existing body of knowledge.

Conclusions

In the present study, the use of Social Network Analysis provided important and weighted interaction patterns that respect the game's ecology and that describe the specificities of, and relationships between, the six game complexes. Moreover, the use of Eigenvector metrics revealed which game events were most influential at each moment of the game by considering the indirect connections with other actions. Our data exhibited some game patterns that are not usually considered in the training process. Indeed, training is usually planned and developed considering the ideal conditions, such as setting the ball through the traditionally considered ideal condition for setting (i.e., Setting Condition A). However, as this study has shown, game patterns are diverse and playing under non-ideal conditions (such as Setting Conditions C and Attack Tempo 3) has a central role in almost all complexes. In this vein, coaches should consider this diversification and prepare teams to face the problems imposed by their opponent, that is, to act in real-game situations, or under non-ideal conditions, in order to optimize team preparation for competition [23, 48].

We also identified a strong relationship between each complex and its subsequent game complexes (e.g., KII with KIII). This suggests that training should consider this complex dependence, such as by analyzing the game scenarios and their probability of occurrence as a result of the actions performed in the previous complex. Prior studies on interaction networks have not used Eigenvector Centrality [7, 15, 32, 33]. Our study thus represents a step forward in considering both direct and indirect connections and delivers a more refined view of an interaction network, which we consider relevant for the understanding of the complex and dynamic nature of team sports.

One limitation of the present investigation is that the tactical systems used by each team, the characteristics of their players, and other situational constraints were not considered. However, the use of Eigenvector Centrality, the consideration of six functional game complexes, and especially the classification of game actions as nodes, has provided a novel approach to interaction networks.

Future studies using Social Network Analysis could make greater use of Eigenvector Centrality from a relational event perspective [49], such as by incorporating game constraints (e.g., players and situational cues) that impact upon the match dynamics. Here, it will also be of remarkable value to explore the game actions performed by players according to their functional specialization in the game [50], and situational variables such as match status [51], quality of opposition [52] and moment of the game [53], among others.

Supporting information

S1 Table. Summary of variables and occurrence in the game.
(DOCX)

S2 Table. Eigenvector Centrality values for Complex 0.
(DOCX)

S3 Table. Eigenvector Centrality values for Complex I.
(DOCX)

S4 Table. Eigenvector Centrality values for Complex II.
(DOCX)

S5 Table. Eigenvector Centrality values for Complex III.
(DOCX)

S6 Table. Eigenvector Centrality values for Complex IV.
(DOCX)
S7 Table. Eigenvector Centrality values for Complex V.
(DOCX)
S1 File. Gephi Data Base with Codes for the different variables: IPS–Initial Position of the Serve; ST–Serve Type (Jump, Jump-Float and Standing-Float); FC–Zone of First Contact; SC Setting Condition; AZ–Attack Zone; AT–Attack Tempo; BO–Block Opposition; KIVB–Number of Available Player Before of Attack Coverage; KIVL–Number of Coverage Lines; KVD and KVF–Downball and Freeball; KVTZ–Target Zone in KV (Attack or Defense Zone).
(ZIP)

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3.2 The need for weighting indirect connections between game variables: Social Network Analysis and eigenvector centrality applied to high-level men's volleyball

The need for weighting indirect connections between game variables: Social Network Analysis and eigenvector centrality applied to high-level men's volleyball

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ABSTRACT

Performance analysis in volleyball has seldom analysed the interrelationships of game actions under the systemic view of distinct game complexes, and how different patterns of game flow emerge. In this study, we used Social Network Analysis with eigenvector centrality to weight direct and indirect relationships between game actions and to assess the similarities and differences between six game complexes in high-level men's volleyball. The study sample comprised 10 matches of the final phase of the 2015 World League (1600 game actions). Results indicated that dividing the game into six complexes and analysing game actions as nodes offers a more detailed understanding of the game and highlights the distinct constraints that typify each game complex. Specifically, the use of eigenvector centrality afforded a more accurate weighting of the variables for each complex. Because off-system situations were predominant in several game complexes, i.e.: Setting Condition C in Complex I (0.36), Complex II (0.55), Complex III (0.80) and Complex V (0.58); Attack Zone 4 and 2 in Complex I (0.30 and 0.28), Complex II (0.48 and 0.51), Complex IV (0.55 and 0.48) and Complex V (0.37 and 0.36); and Attack Tempo 3 in Complex I (0.33), Complex II (0.55) and Complex III (0.66). Our results suggest that coaches should prioritise these situations in training.

ARTICLE HISTORY

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KEYWORDS

1. Introduction

Team sports (TS) are characterised by the interaction of multiple individuals to achieve a collective performance outcome (Duarte, Araújo, Correia, & Davids, 2012). Performance analysis (PA) regularly incorporates match analysis (MA) to establish performance indicators, which can then be used to generate a qualitative and repre- sentative overview of the interaction (cooperation and opposition) between variables that make up a system (Duarte et al., 2012; McGarry, Anderson, Wallace, Hughes, & Franks, 2002; McGarry et al., 2002; Mesquita, Palao, Marcelino, & Afonso, 2013). In this vein, TS can be considered as dynamic systems (McGarry et al., 2002; Walter, Lames, & McGarry, 2007) composed of interconnected subsystems (Stein, 1974) that interact and self-(re)organise in response to changes within the system (McGarry et al., 2002). Understanding how game actions disrupt the balance within a system is one of the complex issues that PA attempts to resolve (Passos, Araújo, & Volossovitch, 2016; Ramos, Lopes, & Araújo, 2017).

Networks consist of nodes and edges (Sasaki, Yamamoto, Miyao, Katsuta, & Kono, 2017), which serve as the primary source of data for many research questions (Newman, 2001). Social Network Analysis (SNA; Mitchell, 1969; Whyte, 1942) was developed as a means to analyse group dynamics and reveal information about systemic behaviour (Bondy & Murty, 1976; Boulding, 1956; Ribeiro, Silva, Duarte, Davids, & Garganta, 2017), particularly the relationships between the actors (or nodes) involved in forming a network (Borgatti, 2005; Wasserman & Faust, 1994). Edges are drawn in the network when there are relationships between nodes (Sasaki et al., 2017). Network Analysis in sports has investigated different network properties. As an example, McLean, Salmon, Gorman, Stevens, and Solomon (2018) analysed the passing networks between football players until they scored a goal through the metric of degree, density and cohesion, among others. Fewell, Armbruster, Ingraham, Petersen, and Waters (2012) examined degree centrality, entropy and flow centrality to characterise the game of basketball, considering players as nodes and ball movements' edges revealing the leading role and distribution patterns of the centralised ball in the point guard. The vast majority of such studies specified the players/agents as nodes, but it is also possible to consider game variables as nodes and their relationships as edges, as has been done in a few selected studies (e.g. Hurst et al., 2017; Loureiro et al., 2017).

Among some common concepts in SNA, graph consists of a set of actors (nodes) connected by edges according to some relation type; a sequence of one or more edges is called path, so when two nodes connect they form a dyad which can be weighted or unweighted connections. Directed graph (or Digraphs) the edges between nodes have a direction, while undirected connections between nodes have no direction. Centrality indicators such as: Degree Centrality counts the number of direct connections of a node (in-degree the connection arrives to a node, out-degree the connection leaves this node and is directed to another) (Freeman, 2004; Ramos et al., 2017; Wäsche, Dickson, Woll, & Brandes, 2017). Eigenvector centrality weights both the direct and indirect connec- tions of nodes, thereby revealing the most central nodes within the network (Bonacich & Lloyd, 2001; Wasserman & Faust, 1994).

The goal of this work was to understand the patterns of game flow in high-level volleyball, considering the interdependency of the six game complexes. The combination of a com- prehensive analysis of the game divided into six complexes, the application of Eigenvector metrics to weight indirect connections in addition to direct connections, and the considera- tion of game actions as nodes all contribute to a novel approach within research in PA.

2. Material and methods

2.1. *Study design*

The first step of research was to create an analysis worksheet (see *Data Collection* subsection) that contained the necessary variables to achieve the research objective, as well as comple- mentary information (matches, scores, etc.). Through the macro-function instantly after the occurrence of a certain action, the information was catalogued in codes already in the necessary format for the cataloguing of each variable. Three observers (see *Training Protocol for the Observer*) underwent 3 months of training prior to analysis of the official study sample, using a random sample of high-level men's and women's volleyball matches, in order to test the instrument and we can find possible analysis and spreadsheet failures. In this way, we performed two reliability tests in this period (one involving the test sample and the other with the official sample) that allowed for the necessary adjustments of the instrument variables and the exclusion of an inconsistent variable (receiving line) and another unnecessary for the sample (Reception Player). Thus, 11 variables were included in the analysis worksheet. The official game data (see *Sample*) was transported to SPSS (see *Data Analysis*) to verify a descriptive data analysis, error checking, frequency, among others, and later the nodes were included in the Gephi program, where the counting of relations of each variable formed the edges and, finally, the global network.

2.2. *Sample*

The sample comprised 9 of the 10 matches from the final phase (the last week of competition with two matches between Group A teams, three matches between Group B teams, two semi-finals and the finals for first–fourth place) of Group 1 from the 2015 men's World League. This was disputed between the men's national teams of Brazil, the USA, France, Poland, Italy and Serbia. Group 1 corresponds to the first division. We did not include Groups 2 or 3 (which correspond to the second and third divisions, respectively) in our analyses because this would require grouping very distinct levels of playing. We purposefully chose only the highest quality matches in order to capture the game dynamics of the highest levels of play. No standardisation was conducted con- sidering that players do not have the same time in match, since the goal was to perceive collective behaviours, and not individual actions. A total of 37 sets were analysed, corresponding to 1618 plays: 1618 actions in Complex 0 or serve, 1615 in Complex I or side-out, 1045 in Complex II or side-out transition, 408 in Complex III or transition, 125 in Complex IV or attack coverage and 126 in Complex V, Freeball or Downball. The Ethics Committee of the Centre of Research, Education, Innovation and Intervention in Sport, University of Porto, provided institutional approval for this study (CEFADE 16.2017).

2.3. *Variables*

The game was divided into six functional *Game Complexes* (Ks) or subsystems. Specifically, we considered the following complexes; Complex 0 (K0) or serve, Complex I (KI) or side-out (offensive organisation after reception), Complex II (KII) or side-out transition, Complex III (KIII) or transition of transition, Complex IV (KIV) or attack coverage and Complex V (KV) or freeball and downball (Hurst et al., 2016, 2017; Loureiro et al., 2017; Mesquita et al., 2013).

The *Initial Position of Server* (based on Quiroga et al., 2010) could be classed either as zone 1 (Z1), zone 6 (Z6) or zone 5 (Z5; see Figure 1). *Serve type* (adapted from Costa, Afonso, Brant, & Mesquita, 2012; Quiroga et al., 2010) was divided into jump float serve (without ball rotation), jump serve (with ball rotation) and standing float serve (without jumping).

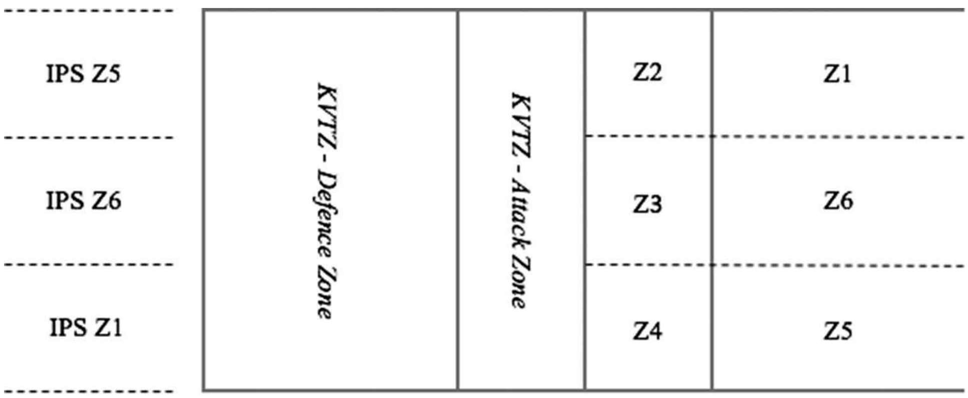

Figure 1. Initial Position of the Server (IPS); KV Target Zone (attack or defence zone) and Fédération Internationale de Volleyball (FIVB) official zones.

The *Zone of First Contact* (reception and defence) followed the six official zones described in the FIVB rules (see Figure 1). *Setting conditions* correspond to the number of attackers that is available before setting and could be defined as A (the setter had all attack options available), B (the setter still could deploy quick attacks, but some attack options such as crossings were not possible) and C (the setter can only use high sets; adapted from Hurst et al., 2017; Loureiro et al., 2017).

The area where the attack was carried out, the *Attack Zone*, was determined using the six official zones stipulated by the FIVB. *Attack Tempo* described the synchronisa- tion between setter and attacker (adapted from Afonso & Mesquita, 2007; Costa et al., 2012): Tempo 1 – the attacker jumped before or at the same time as the set; Tempo 2 – the attacker performed two steps after the set; and Tempo 3 – the attacker waited for the ball to ascend and then performed a three-or-more-steps approach.

For *Block Opposition*, B0 indicated that no blockers opposed the attack. B1 indicated a simple or individual block. B2 indicated a double block, and finally B3 indicated a triple block (adapted from Afonso & Mesquita, 2011). The *Number of Attackers Available pre-KIV* variable (adapted by Laporta, Nikolaidis, Thomas, & Afonso, 2015a, 2015b) describes the number of players available prior to attack coverage. The *number of coverage lines* refers to the imaginary lines between the net and end line occupied by the defenders.

The offensive organisation of a team when the ball is delivered with no possibility of an aggressive intention and thus with less risk to the opponent was described as *Freeball* (Hurst et al., 2017). *Downball* is similar to the freeball condition, but the opponent has the chance to perform a standing spike, and so theoretically the implications are distinct from the freeball condition (based on Selinger & Ackermann-Blount, 1986). *KV Target Zone* referred to the court zone where the ball fell, including offensive zones (zones 2, 3 and 4) and defensive zone (zones 5, 6 and 1). Note that some variables appear in multiple game complexes with different characteristics in each.

2.4. *Data collection*

High-definition (1080p) video recordings of the matches were obtained from youtube. com and laola.tv. These films had a lateral side view of the court, with the camera aligned with the net. The camera moved during the film to accompany the movement of the ball and the categorisation of the variables took this movement into account. Each game action was classified according to the complex in which it occurred and data were input into an Excel spreadsheet (Microsoft Excel 2017 – Microsoft Office Professional 365 Version 15.30, E.U.A.).

2.5. *Training protocol for the observers*

The observers for the present study were four volleyball coaches, each with experience at the national level. These observers were trained to score game actions and input data into the Excel spreadsheet according to our definitions over 3 months, during which time four reliability tests, each conducted with different samples, were conducted to adjust the variables and categories and to ensure the trustworthiness of the instrument (Hughes, Cooper, & Nevill, 2002). All but one of the variables showed values higher than 0.75 across the four tests (Fleiss, Levin, & Paik, 2013). The exception, *Type of Received Line*, was eventually removed from the final version of the instrument.

2.6. *Data analysis*

We first conducted descriptive data analysis using SPSS for Mac (Version 24, IBM®, NY, U.S.A.) to assess data quality, input errors and global features of the data such as frequencies of occurrence. The corrected file was then exported. We conducted SNA using Gephi 0.9.1 for Mac (MacRoman, Compiègne, France). The relationships between the nodes were counted as they occurred throughout the game. Node size and edge thickness were determined by varying the program according to the different nodes' relationships. It should be noted that these values represent arbitrary units that decrease or increase according to the different Eigenvector values and are merely a device to provide a better visual experience of the graph.

2.7. *Data reliability*

Inter-observer reliability was assessed using 10% of the total sample (a total of 160 actions) as suggested in the literature (Tabachnick & Fidell, 2007). This analysis revealed Cohen's Kappa values of between 0.80 and 1.0 for the study variables, which exceeds the threshold of 0.75 proposed by specialised literature (Fleiss et al., 2013).

3. Results

We created a global network between the variables of the six complexes using eigen- vector centrality (Figure 2). Nodes were labelled according to their corresponding complex (K0, KI, KII, KIII, KIV and KV) and an abbreviation of the variable (e.g. KIIAT2 denotes Attack Tempo 2 in complex 2). Together with the eigenvector value,

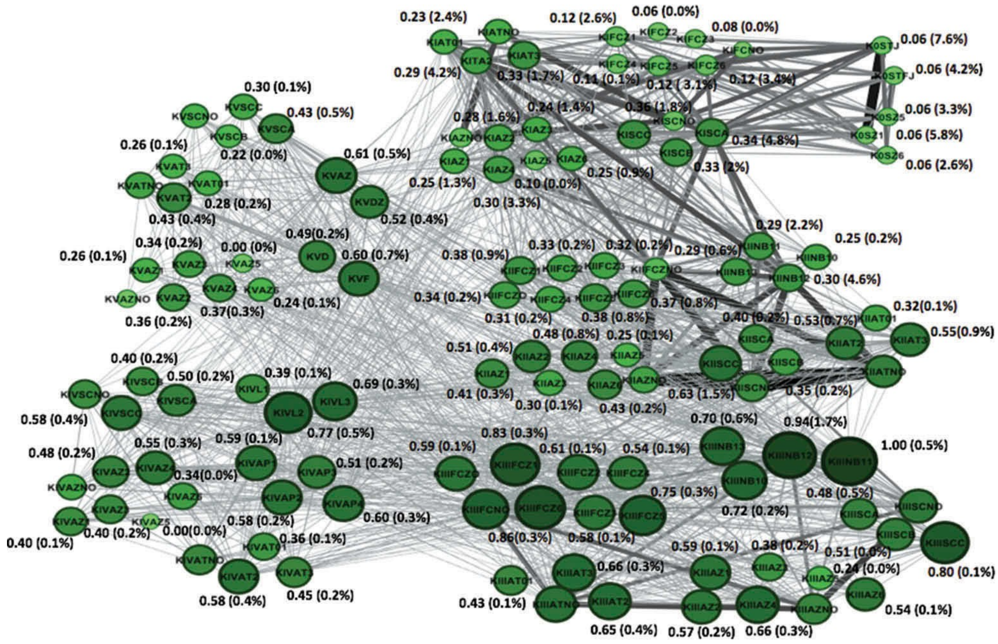

Figure 2. Network with eigenvector centrality for all complexes. The variable can assume: IPS – Initial Position of the Server; ST – Serve Type (jump, jump-float and standing-float); FC – First Contact; SC Setting Condition; AZ – Attack Zone; AT – Attack Tempo; BO – Block opposition; KIVB – Number of Attackers Available Before KIV; KIVL – KIV Lines; KVD and KVF – Downball and Freeball; KVTZ – KV Target Zone (attack or defence zone).

the percentage of occurrence of each variable will be presented (e.g. 0.26–4% indicates that the variable obtained the eigenvector value of 0.26 and had a 4% occurrence in the global sample). Because the analysis of complex networks is not always clear, the following section will highlight the main results as they related to each game complex. In K0, or the serve complex, standing float serves presented the lowest eigenvector value (0.00) for the variable *Serve Type*, with jump float serve and jump serve having exhibited the same eigenvector value (0.06). There was no difference in eigenvector

value between the three zones (0.06) defined for *Initial Position of the Server*.

For KI, setting condition C (0.36) and attack tempo 3 (0.33) had the highest eigenvector values for their corresponding variables. In terms of *Zone of First Contact*, eigenvector values were equally low for zones 1, 6 and 5 (0.12). Zone 4 (0.30), followed by zone 2 (0.28), had the highest eigenvector values for this variable.

Within KII, setting condition C (0.63) also presented the highest eigenvector value for the variable *Setting Conditions*. For *Attack Tempo*, the highest two eigenvector values were for tempo 3 (0.55) and tempo 2 (0.53), respectively. In terms of *Attack Zone*, zones 2 (0.51) and 4 (0.48) had the highest two eigenvector values, followed by zones 6 (0.43) and 1 (0.41).

Regarding KIII, setting condition C (0.80) exhibited the highest eigenvector value for *Setting Conditions* (and indeed the highest value across all complexes). For the variable *Attack Tempo*, tempo 3 (0.66) and tempo 2 (0.65) had similar values, both higher than for tempo 1 (0.48). In terms of *Attack Zone*, zones 4 (0.66) and 1 (0.59) showed the highest eigenvector values, followed next by zone 2 (0.57) and zone 6 (0.54). For *Block Opposition*, nodes representing attacks opposed by a single blocker (B1) or by two blockers (B2) had higher eigenvector values than those representing unopposed blocks (B0; 0.72) and attacks opposed by three blockers (B3; 0.70).

In KIV, setting condition C once again exhibited the highest eigenvector value (0.58) across *Setting Conditions*, followed by setting condition A (0.50). For *Attack Tempo*, tempo 2 (0.58) had the highest eigenvector value, followed by tempo 3 (0.45). For the *Attack Zone* variable, zone 4 showed the highest eigenvector value (0.55), followed by zone 2 (0.48). In terms of the *Number of Coverage Lines*, nodes representing two (0.77) and three (0.69) coverage lines had high eigenvector values compared to that represent- ing one line (0.39).

The pattern of values was slightly different for KV. For *Setting Conditions*, the highest eigenvector value was observed for condition A (0.43), followed by condition B (0.22). In terms of *Attack Zone*, zone 4 (0.37) and zone 2 (0.36) had the highest values, followed closely by zone 3 (0.34). For *Attack Tempo*, tempo 2 (0.43) had the highest eigenvector value, followed by tempo 1 (0.28). Finally, *KV Target Zone* for freeball (0.60) appeared to be compatible with downball (0.49).

4. Discussion

The study of TS is based on investigating individual and team dynamics. Toward this goal, PA serves to promote an understanding of the game in a systematic manner. In the present study, we sought to understand the relationships between game variables belonging to the six game complexes (Ks) of volleyball using SNA and eigenvector centrality.

Our results revealed differences and similarities between Ks and highlighted the relevance of analysing game actions as nodes. The present study thus departs from the player-centred approaches used in most sports research (e.g. Clemente, Martins, Mendes, & Silva, 2016; Duch, Waitzman, & Amaral, 2010) and contributes to the currently developing work in this field (Hurst et al.,2016, 2017; Loureiro et al., 2017). Specifically, the results showed, in men's elite volleyball, that teams played in-system situations in KI – particularly related to Attack Zone, Attack tempo and Setting Conditions – while in KII there was a prevalence of off-system actions.

First, while quicker attack tempos are usually associated with impaired block cohe- sion (Afonso & Mesquita, 2011; Costa et al., 2016), our results showed that slower attack tempos (AT3) were predominant in KI, KII and III, i.e. in the most commonly occurring Game Complexes. Interestingly, although KV had more "in-system" playing (i.e. with Setting Condition A being more central), attacks in the extremities of net (i.e.

Z.2 and Z.4) still presented the greatest eigenvector values. This indicates that the teams preferred to adopt safer game strategies, possibly to lower the risk of error (Loureiro et al., 2017; Mesquita et al., 2013).

Actions performed under ideal setting conditions can influence the creation of better attack options (Araújo, Moraes, Coutinho, & Mesquita, 2012) and decrease the continuity of rally (Costa, Afonso, Vieira, Coutinho, & Mesquita, 2014). That said, our results show that playing under non-ideal setting conditions (i.e. Setting Condition C) was central in most game complexes (with the exception of KV). Loureiro et al. (2017) analysed KI, KII and KIII complexes during the 2015 World Cup, and concluded that teams play "in- system" during KI (i.e. Setting Condition A), while in KII and KIII the teams play "off- system" (i.e. Setting Condition C). Our results contrast with this because they show "non- ideal" setting conditions in all three major complexes. It is possible that this is related to the increase in difficulty imposed on the serve (Paulo, Zaal, Fonseca, & Araújo, 2016; Silva, Lacerda, & João, 2014), and suggests that the regularities of the game change over time. An implication of this is that researchers on MA need to constantly update their scrutiny of the game. The fact that only KV revealed better setting conditions ("in-system" playing) is concurrent with at least on past study (Hurst et al., 2017), although this study was conducted in women's rather than men's volleyball.

Overall, using SNA in volleyball seems to be an important way to consider the interdependence of the game actions because it implies a relational perspective of performance (Emirbayer, 1997). For instance, while in-system playing (i.e. the setter has ideal conditions for setting an attack) is favoured in training, off-system situations are not often considered. Because off-system playing is prevalent at the highest levels of practice, it should be a core aspect of training, including in youth categories, as a means to adequately prepare athletes for the demands of competition. Indeed, this is not merely an issue of tactical and/or technical preparation but also one of fostering an appropriate mindset for competition. In short, our results suggest that coaches should prioritise off-system situations in training so that athletes develop an ability to solve problems imposed by opponents. Ultimately, this should optimise the training process and help prepare athletes for competition.

Although male volleyball does not have a tradition of long rallies (Costa et al., 2012), our results also imply that the training should emphasise transitions (KII and KIII), especially those with attack actions of slower tempos (3 and 2) against a higher number of blockers (double and triple).

Our results show that this zone had lower eigenvector values than the attack zones located at the extremity of the network. This indicates that it is important for training to incorporate the less favourable conditions (e.g. Setting Conditions B).

Finally, it was evident from our data that future research on MA in volleyball should consider at least six functional game complexes, as suggested initially by Monge (2003, 2007), rather than following the trend in past research to group these into two major complexes (e.g. side-out vs. transition). Grouping complexes in this manner might average out the differences in relationships between game actions and result in a delusive analysis of the game that does not correspond to the regularities that occur in each complex. Thus, knowing the variables' behaviour in each game complex will aid in the optimisation and effectiveness of the team in training and/or game, or even surprising trying to modify it. Playing in off-system situations indicates a path to be considered, such as the variable Setting Condition that we always try to have better attack conditions to reach the point, but the game with few attack options (SC C) has shown to be a regularity in almost all moments of the game (KI, II, KIII and V). In addition, one of the limitations of the study was not to consider the efficacy of rallies, but only that of plays. Since the rally encompasses all the plays within a given point, grouping plays into rallies would provide an additional level of analysis.

Disclosure statement

No potential conflict of interest was reported by the authors.

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3.4 Do distinct game patterns influence play efficacy in high level women's volleyball? A study using Eigenvector Centrality

Do distinct game patterns influence play efficacy in high level women's volleyball? A study using Eigenvector Centrality[4]

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Abstract

In volleyball, it is often assumed that distinct game patterns may influence the outcome of the play differently. However, hints have emerged in the literature suggesting that play efficacy may rely more on the quality of individual attacking actions, and not on game patterns. Therefore, the purpose was to scrutinize if and how game patterns influence play efficacy in high-level women's volleyball. Eigenvector Centrality was assessed to integrate direct and indirect relationships (edges) between games actions (nodes) into a comprehensive analysis of game patterns. Thirteen matches from the women's World Grand Prix'2015 were analysed, in a total of 46 sets and 2,016 plays. Actions were categorized according to game complex (i.e., K0 to KV), and the efficacy of each play comprised three levels: 0 (error), 1 (continuity) and 2 (scoring a point). Results showed that, in women's volleyball, all levels of efficacy presented similar game patterns, meaning that such patterns may not be good predictors of the outcome. Although there were minor differences, categories belonging to variables such as Setting Condition, Attack Tempo and Attack Zone presented similar centrality values for all levels of efficacy. Therefore, results suggest that the individual skills in attack may play a more relevant role than the game patterns in determining efficacy. This contradicts the dominant view and reinforces certain insinuations that have arisen in selected literature. We suggest that these results are verified in different competitions, to substantiate if they constitute true features of the game or represent idiosyncrasies of a specific sample.

Keywords: *Performance Analysis; Network Analysis; Indirect Connections; Game Complexes.*

Introduction

The quest for improving sport performance has motivated research focused on using Match Analysis (MA) to uncover performance indicators that provide a broader understanding of the game and, consequently, deliver novel know-how and tools for optimizing training processes (Garganta, 2009). Analysis of the efficacy of game actions has been highly researched in sports (Garganta, 2009; Mesquita, Palao, Marcelino, & Afonso, 2013; Silva, Marcelino, Lacerda, & João, 2016). Especially in high level competitions, the proficiency in the main game actions provides a competitive edge that might determine the outcome of a match (Paulo, Zaal, Seifert, Fonseca, & Araújo, 2018). In attempting to find correlates of efficacy, research has focused on the analysis of movement patterns, player position, competitive level, scoring system, gender, opposition quality, match status, match local, match outcome, among others potentially contributing factors (Fernandez-Echeverria, Mesquita, González-Silva, Claver, & Moreno, 2017; Marcelino, Sampaio, & Mesquita, 2011; Silva et al., 2016).

However, the question of how different game patterns correlate to efficacy levels is still underexplored in empirical research using Match Analysis, especially in volleyball. And conflicting findings have emerged in the literature. For example, while a wide body of research has suggested that different game patterns may associated with debilitated opposition and therefore increase the chances of success (Afonso, Mesquita, & Coutinho, 2008; César & Mesquita, 2006; Marcelino, Mesquita, & Afonso, 2008; Mesquita, Guerra, & Araújo, 2002), a few hints are arisen proposing that it might not always be the case in high-level women's volleyball (Afonso & Mesquita, 2011; Mesquita & Graça, 2002). These latter studies have suggested that play efficacy may be largely independent of game patterns, instead relying more strongly on the individual skill of the attackers (Afonso & Mesquita, 2011; Mesquita & Graça, 2002). This might be explained by the fact that volleyball is a sport where the teams cannot invade the opponents' space, and therefore the attacker will ultimately have some room for acting without a very pressing opposition (Mesquita & Graça, 2002; Queiroga, Matias, Greco, Graça, & Mesquita, 2005). Therefore, these few selected studies may entice the fact that maybe mainstream understanding of these phenomena are, at best, incomplete. And science often advances precisely when and where inconsistencies arise.

In this vein, Social Network Analysis (SNA) is a method that has been regarded with growing interest in the sports context (Wäsche, Dickson, Woll, & Brandes, 2017), providing a systemic network view through the establishment of nodes and edges connecting them (Boulding, 1956). SNA reveals a global network through the structural features of the actors (e.g., position within the network, most important information transmitters, among others) (Yamamoto & Yokoyama, 2011). Although there are six-dimensions in a conceptual typology of SNA applications (see Wäsche et al. (2017), two dimensions have been widely used in sport, namely competition networks (informing about the competitive outcome through patterns of interaction between athletes and/or teams) and interaction networks (how the relationships established between the players alter the outcome). In this context, by allowing nodes to be treated as game actions and their relations as edges, interaction networks can afford an understanding of the game that is independent of the players who performed the actions (Hurst et al., 2017; Laporta, Afonso, & Mesquita, 2018a; Loureiro et al., 2017).

Furthermore, networks can be better attuned to a systematic analysis by weighting the indirect connections in addition to direct connections. In this scope, Eigenvector Centrality is a measure that assists in establishing a more complete relational overview of a network, since it properly weights both the direct and indirect connections of the nodes (see Bonacich & Lloyd, 2001; Wasserman & Faust, 1994). In team sports, game actions can produce diverse direct and indirect consequences (Cotta, Mora, Merelo, & Merelo-Molina, 2013). As such, calculation of Eigenvector Centrality implies a standardization process (Bonacich & Lloyd, 2001; Freeman, 1978), where all the actions of all the game complexes contributed to analysis, thus providing a more precise view of how the variables contribute and influence different levels of effectivity. Thus, this centrality measure will show the results of the interaction patterns between the variances (Duch, Waitzman, & Amaral, 2010), helping to find out if the analysed actions influence the effectiveness of the team. Indeed, this has already been attempted in some of our previous research (Hurst et al., 2017; Hurst et al., 2016; Laporta et al., 2018a; Laporta, Afonso, & Mesquita, 2018b; Loureiro et al., 2017).

The sheer complexity of such treatment might, however, render the analysis overly intricate. As such, we chose to investigate volleyball, since it presents a more regular structure and predictable game patterns than other team sports (Mesquita et al., 2013; Palao, Santos, & Ureña, 2004), mainly due to limitations imposed by the rules. Specifically, the impossibility of grabbing the ball and the limitation of three contacts per ball possession (excluding a few exceptional situations, such as the touch on the block) narrows the possibilities of game patterns (Afonso & Mesquita, 2011; Mesquita et al., 2013). Volleyball is composed of six interdependent subsystems or game complexes, (Laporta et al., 2018a): serve or K0, side-out or KI (reception, setting and attack), side-out transition or KII (blocking, defence, setting and attack), transition or KIII (blocking, defence, setting and attack), attack coverage or KIV (offensive organization after the coverage action) and freeball/downball or KV (offensive organization after freeball or downball) (Hurst et al., 2017; Hurst et al., 2016; Loureiro et al., 2017).

Therefore, the purpose of this study was to understand if and how different game patterns impact upon the efficacy of each play in high-level women's volleyball, addressing inconsistencies that have arisen in the literature. While previous studies have analysed game patterns in high-level volleyball through SNA and Eigenvector Centrality (Hurst et al., 2017; Hurst et al., 2016; Laporta et al., 2018a, 2018b; Loureiro et al., 2017), and already considering the six functional game complexes of this sport, to our knowledge none have use this metrics to relate game patterns to efficacy.

Materials and Methods

Participants

The sample totalled 2,049 plays (46 sets) from 13 women matches of the Final Phase of the 2015 Edition of the World Grand Prix (teams: Brazil, USA, Italy, China, Japan and Russia), with 2,016 actions in K0, 1,396 in KII, 1,384 in KIII, 207 in KIV, and 197 in KV. The network was built with 127 nodes and 2153 edges. A play should not be mistaken for a rally: the former refers to each ball possession on the part of a team, while the latter is the collection of plays within the same disputed point. This Study was approved by the Ethics Committee at the Centre of Research, Education, Innovation and Intervention in Sport of University of Porto (CEFADE 16.2017).

Measures

Game Complex (K) encompassed: K0 (serve), KI (side-out), KII (side-out transition), KIII (transition), KIV (attack coverage) and KV (freeball/downball) (Hurst et al., 2017; Laporta et al., 2018a; Loureiro et al., 2017). In Complex 0, *Initial Position of the Server* (i.e., Zones 1, 6 or 5) (Quiroga et al., 2010) and *Serve Type* were considered: float jump serve (i.e., without ball rotation), jump serve (i.e., with ball rotation) and standing serve (i.e., without jumping) adapted from Costa, Afonso, Brant, and Mesquita (2012).

Zone of First Contact emerged in Complexes I, II and III and followed the six zones defined of the court as defined by FIVB rule, but added the Others Zone (OT), corresponding to the area outside the court, where the athlete can recover the ball after a touch in the block, for example. In complexes II and III, *Block Opposition* was adapted from Afonso and Mesquita (2011): i) BO - no-block, ii) B1 - simple Block, iii) B2 - double block; and iv) B3 - triple block.

The following variables appear in complexes I, II, III, IV and V. *Setting Condition* evaluates the relative quality of the first contact, linking it with the attacking options: (i) A - all attack options available; (ii) B – some attack options, such as crossings, are not possible, but quick attacks still constitutes a possibility; and (iii) C – the setter can only use high sets (adapted from Hurst et al., 2017). *Attack Zone* was evaluated according to the FIVB official zones – (zones 1 to 6).

Attack Tempo concerns the synchronization between setter and attacker: i) tempo 1 - attacker jumped before/same time to the set; ii) tempo 2 - two steps approach is performed by the attacker after the set; and iii) tempo 3 - the attacker waited for the ball (ascend movement) and after that execute a three- or more-steps approach (simplified from Costa et al., 2012).

Specifically in Complex IV, the following variables were considered: *Available Players Before Attack Coverage* showed the available players to attack before of the attack coverage happened (adapted by Laporta, Nikolaidis, Thomas, & Afonso, 2015); *Number of Coverage Lines* was analysed the imaginary lines (from the net until the endline) created by the players in defence position at the attack moment Laporta et al. (2015). In Complex V, the *Freeball* (offensive organization after the a ball that will have to be returned softly by the opponent, due to poor conditions for performing the third contact) and *Downball* (attacker was unfavourable to attack, but still can perform a standing spike)(Loureiro et al., 2017); and *KV Target Zone* (zone where the ball landed being offensive or defensive zone).

The Efficacy of each game complex reported the outcome of each complex: i) E0 - error; ii) E1 - continuity; and iii) E2 – scoring a point (adapted from Costa, Afonso, Vieira Barbosa, Coutinho, & Mesquita, 2014).

Design and Procedures

Matches were obtained from the sites *laola.tv* and *youtube.com,* recorded from a lateral side view of the court (aligned with the net with movement on both sides) in high definition (1080p).

An analysis worksheet (Microsoft® Excel® 2017 - Office Professional 365 Version 15.30, U.S.A.) was created with the necessary variables to answer the objectives of the study. The data were recorded using the macro function to catalogue the required codes in the appropriate cells. To test the instrument, three observers with experience in the area were trained for three months and three instrument reliability tests were performed prior to this study, in which in the final 12 variables (described above) have reached values of Cohen's Kappa above 0.75 (Fleiss, Levin, & Paik, 2013).

After initial registration, data were exported and examined using SPSS® for Mac (Version 22, IBM®, E.U.A.). A descriptive analysis was conducted to ensure data quality (verify input errors, data frequency and others). Finally, Social Network Analysis techniques were applied using Gephi© 0.8.2-beta for Mac (Version 10.10.3, MacRoman, France). Nodes appear in the periphery of the network so that all interactions can be clearly apparent. Nodes' size and colour were perfected to visually reflect the magnitude of their Eigenvector values. The nodes' size was stipulated between 500 (minimum) to 2,500 (maximum), wherein the Eigenvector measure was used to identify the most influential nodes in the network. Edges were also depicted with a stronger intensity in order to better reflect Eigenvector values.

Regarding data reliability of the definitive data collection, the inter-observer reliability was calculated with the analysis of 10% of the total sample (total of 210 actions) as suggested in the literature Fleiss et al. (2013), having presented Cohen's Kappa values above 0.75 for all variables

Results

The established networks present the Eigenvector values for each level of efficacy (i.e., 0, 1 or 2). The network below (Fig 1) reveals game patterns for Efficacy 0 (Error).

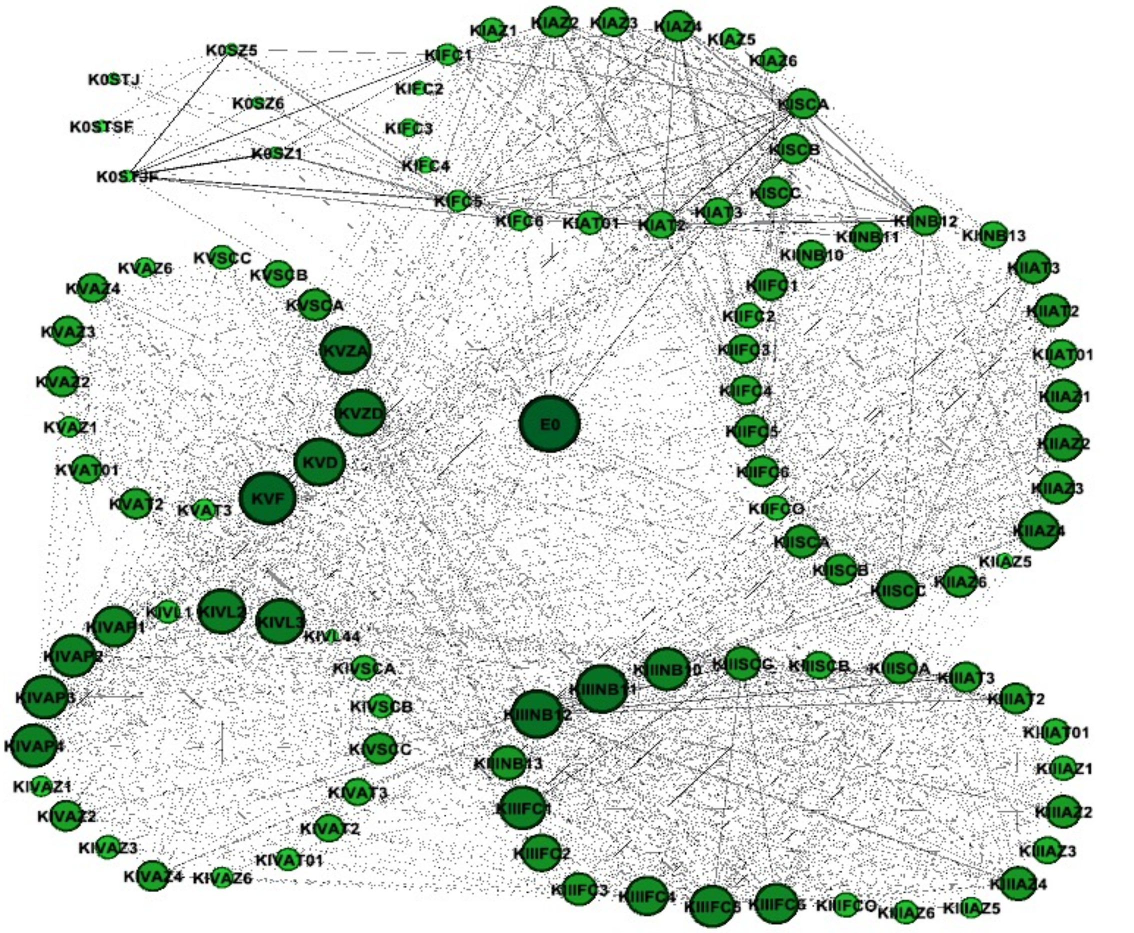

Fig 1. Network with Eigenvector Centrality for all variables related to the efficacy 0 in women's volleyball. Terminology: in each node, codes are represented by the name of complex (e.g., KII), followed by the variable and its category (e.g., KIIAZ6 indicates that the action occurred in complex II, the variable in question was Attack Zone, and the category is Zone 6). Codes for the different variables: IPS – Initial Position of the Serve; ST – Serve Type (Jump, Jump-Float and Standing-Float); FC – Zone of First Contact; SC Setting Condition; AZ –Attack Zone; AT – Attack Tempo; BO – Block Opposition; KIVB – Number of Available Player Before of Attack Coverage; KIVL – Number of Coverage Lines; KVD and KVF – Downball and Freeball; KVTZ –Target Zone in KV (Attack or Defense Zone). E - Actions Efficacy.

Eigenvector values have highlighted, for *Efficacy 0* (i.e., error; Fig 1): (i) jump float serve (0.06) in K0; (ii) Setting Condition C in KI (0.36), KII (0.52), KIII (0.65) and KIV (0.48); Setting Condition A in KV (0.46); (iii) Attack Zones 4 and 2 in KI (0.30 and 0.39), KII (0.41 and 0.43), KIV (0.52 and 0.49), KIV (0.46 and 0.40), and KV (0.31 for both); in KIII, Attack Zone 4 (0.48) was followed by zone 1 (0.48); (iv) Attack Tempos 2 and 3 in KI (0.39 both), KII (0.51 and 0.51), KIII (0.46 and 0.45), and KIV (0.39 and 0.38); Attack Tempos 2 and 1 in KV (0.45 and 0.41).

The game patterns related to Efficacy 1 (Continuity) is presented in Figure 2.

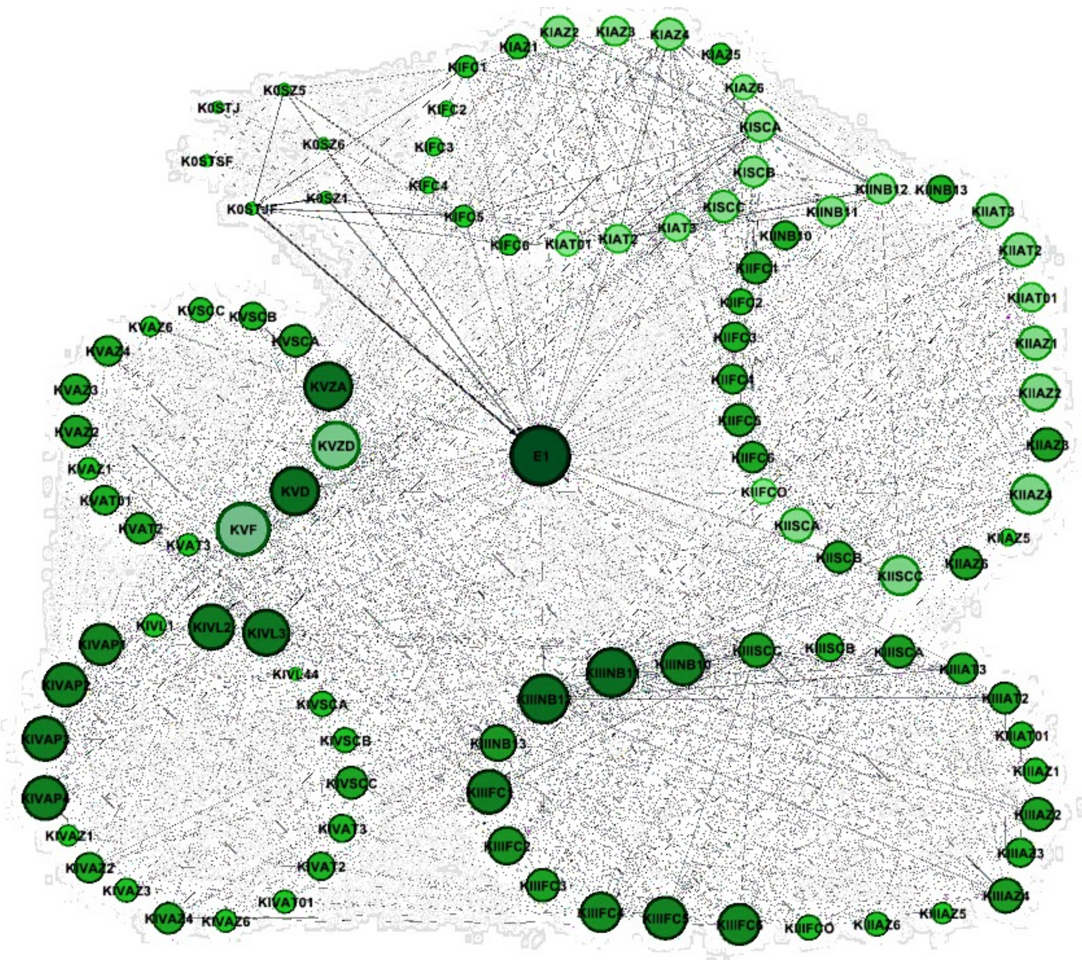

Fig 2. Network with Eigenvector Centrality for all variables related to the efficacy 1 in women's volleyball. Terminology: in each node, codes are represented by the name of complex (e.g., KII), followed by the

variable and its category (e.g., KIIAZ6 indicates that the action occurred in complex II, the variable in question was Attack Zone, and the category is Zone 6). Codes for the different variables: IPS – Initial Position of the Serve; ST – Serve Type (Jump, Jump-Float and Standing-Float); FC – Zone of First Contact; SC Setting Condition; AZ –Attack Zone; AT – Attack Tempo; BO – Block Opposition; KIVB – Number of Available Player Before of Attack Coverage; KIVL – Number of Coverage Lines; KVD and KVF – Downball and Freeball; KVTZ –Target Zone in KV (Attack or Defense Zone). E - Actions Efficacy.

Eigenvector values have highlighted, for *Efficacy 1* (i.e., continuity): (i) jump-float (0.06) in K0; (ii) Setting Condition C in KI (0.45), KII (0.60), KIII (0.50) and KIV (0.46); Setting Condition A in KV (0.46); (iii) Attack Zone 4 in KI (0.45), KII (0.60), KIII (0.50), and KIV (0.43); AZ 2 in KV; (iv) Attack Tempo 2 in KI (0.37), KII (0.49), KIII (0.44), KIV (0.37), and KV (0.43).

The game patterns associated to Efficacy 2 (point) is presented in Figure 3.

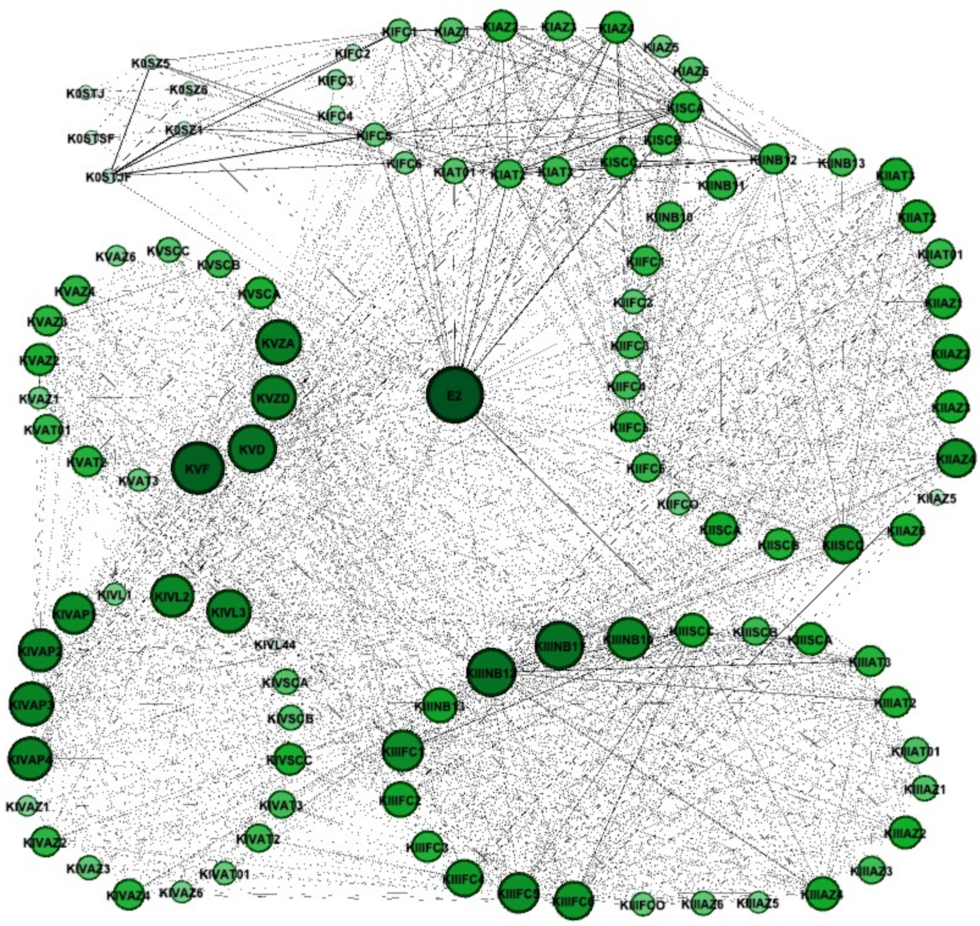

Fig 3. Network with Eigenvector Centrality for all variables related to the efficacy 2 in women's volleyball. Terminology: in each node, codes are represented by the name of complex (e.g., KII), followed by the variable and its category (e.g., KIIAZ6 indicates that the action occurred in complex II, the variable in question was Attack Zone, and the category is Zone 6). Codes for the different variables: IPS – Initial Position of the Serve; ST – Serve Type (Jump, Jump-Float and Standing-Float); FC – Zone of First Contact; SC Setting Condition; AZ –Attack Zone; AT – Attack Tempo; BO – Block Opposition; KIVB – Number of Available Player Before of Attack Coverage; KIVL – Number of Coverage Lines; KVD and KVF – Downball and Freeball; KVTZ –Target Zone in KV (Attack or Defense Zone). E - Actions Efficacy.

Our results further highlighted, for *Efficacy 2* (i.e., point): (i) jump-float (0.06) in K0. (ii) Setting Condition C in KI (0.46), KII (0.61), KIII (0.51) and KIV (0.46); SCA in KV (0.48); (iii) Attack Zones 4 and 2 in KI (0.45 and 0.45 respectively), KII (0.61, 0.56), KIII (0.51, 0.48), KIV (0.44, 0.44); Attack Zone 2 in KV (0.43); (iv) Attack Tempo 3 in KI (0.38), KII (0.50), KIII (0.44), KIV (0.38), and KV (0.44).

Discussion and Conclusion

The aim of this study was to understand if game patterns impacted upon the efficacy of each play. While the mainstream view is that distinct game patterns affect efficacy level (e.g., Afonso et al. (2008); Marcelino et al. (2008), a few dissonant results have emerged in the literature (e.g., Afonso & Mesquita, 2011; Mesquita & Graça, 2002), suggesting that maybe individual skill (and not game patterns) are more determinant for efficacy level. To address these inconsistent findings, we used a framework of analysis considering the six functional game complexes usually described for volleyball (e.g., Laporta et al. (2018a, 2018b), applying it to high-level women's volleyball. Previous research has applied Social Network Analysis and Eigenvector Centrality to consider the direct and indirect relational dynamics, while at the same time treating game actions as nodes (Hurst et al., 2017; Laporta et al., 2018a, 2018b; Loureiro et al., 2017). Here, we took such analysis one step further, by relating game patterns to distinct efficacy levels. Instead of a unitary network, averaging out the reality of the game, one network per efficacy level was created, to better provide a contrast between the networks that relate to each efficacy level.

Our results unequivocally showed that game patterns were highly similar for all the three levels of efficacy, i.e. the analyzed variables and their relationships presented roughly the same behavior regardless of efficacy level. First and foremost, playing under non-ideal conditions (i.e., Setting Condition C) was a core feature associated with E0, 1 and 2 in complexes I-IV, evidencing the need for teams to be capable of playing a large portion of time under non-ideal or off-system conditions, and therefore reinforcing previous studies in women's volleyball (Hurst et al., 2017; Hurst et al., 2016; Laporta et al., 2018a, 2018b). This result further suggests that play efficacy will be largely independent of game pattern. Similarly, the same occurred even when Setting Condition A was predominant. For example, in KV, Setting Condition A was the most central category, but again this occurred regardless of efficacy level, meaning that the quality of the first contact and therefore the Setting Condition was not determinant for success. These results seem to corroborate previous findings in women's volleyball (Afonso & Mesquita, 2007; Afonso, Mesquita, & Marcelino, 2008), and concur to suggest that individual skill may overcome collective game patterns. This is even more interesting as these aforementioned studies used different methods and variables than those used in this particular research. Additionally, attacks on the extremities of the net (i.e., zones 2 and 4) and using slower attack tempos (i.e., tempos 2 and 3) were central across all efficacy levels. These results are also in line with previous studies in women's volleyball (Afonso & Mesquita, 2011; Moutinho, Marques, & Maia, 2003).

A few results may, however, derive simply from the fact a single category of given variable being highly predominant; for example, the Jump Float-Serve (K0) is highly prevalent in high-level women's volleyball (Hurst et al., 2016; Palao, Manzanares, & Ortega, 2009), and the same occurred in this study. Therefore, it comes as no surprise that this category presented greater centrality than every other type of serve for all levels of efficacy. And, despite the similarities, there were minor differences in game patterns between the three levels of efficacy. For example, the serve from position 6 was more central in E0, therefore relating more to errors than to continuity or scoring a point. However, the differences are minute and clearly in the minority, meaning that they likely constitute random findings, instead of reflecting a true game pattern.

In sum, the centrality maps (weighting both direct and indirect connections between the nodes) were highly similar for all three levels of efficacy, implying that game patterns are highly regular in volleyball, regardless of the outcome, which is coherent with the highly rigid and predictable functional structure of volleyball (Afonso et al., 2008; Mesquita, 2005). This further suggests that individual skill in attacking actions may play a more relevant role than game patterns, at least where efficacy of the play is considered. Similar findings have been suggested by José Afonso and Mesquita (2011), who analysed a number of game variables capable of influencing block cohesiveness and attack efficacy in women's volleyball. The authors found that several variables indeed influenced block cohesiveness (e.g., reduced number of blockers opposing the attack; late or broken block), but failed to alter the values where the efficacy of the attack was considered. Since volleyball does not allow invasion of the opponent's court, the blocker cannot interfere directly with the attacker's action. Therefore, the attacker's individual skill and privilege of contacting the ball first might surpass the importance of how the play unfolded up until that point (Mesquita & Graça, 2002; Queiroga et al., 2005).

Overall, we have used a more refined approach to analyzing the game of volleyball (e.g., weighting both direct and indirect connections between game actions; considering the six functional game complexes described in the literature), in attempting to address contradictory findings in the literature. Our results clearly support the importance of individual skill in determining attack efficacy in high-level women's volleyball, since game patterns were extremely similar across all levels of play efficacy. This highlights the need to evaluate how situational constraints impact upon individual actions (e.g., match status, moment of the game or set, results or previous individual actions by the same player, type of set, home vs. away match, among many other possibilities). Nonetheless, we strongly recommend that this research is replicated in different competitions and playing levels, to understand if this represents a strong feature inherent to volleyball, or instead constitutes an idiosyncrasy of a few selected samples. Finally, it would also be interesting to apply this rationale and methods to men's volleyball, verifying if similar or disjunct logic applies.

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3.4 Using social network analysis to assess play efficacy according to game patterns. A game-centred approach in high-level men's volleyball

Using social network analysis to assess play efficacy according to game patterns. A game-centred approach in high-level men's volleyball[5]

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Abstract

Match Analysis has provided valuable insights for understanding performance, both from a player-centred and game-centred approaches. In this vein, Social Network Analysis has delivered powerful contributions, especially with its most recent game-centred approaches and the weighting of both direct and indirect connections between game actions. In this manuscript, the goal is to expand these applications, analysing whether different networks correlate with distinct levels of play efficacy. This novel rationale was applied to high-level men's volleyball, having considered six functional game complexes. Social Network Analysis was applied with calculation of Eigenvector Centrality, and one network or map was created for each level of play efficacy: 0 (error), 1 (continuity) and 2 (scoring a point). The sample was composed by 1,618 game actions (9 matches from the 2015 World League Finals), categorized according to game complex (i.e., K0 to KV) and generating one network per efficacy level, including all game complexes. Against our expectations, results showed similar networks for all levels of efficacy, suggesting that (i) collective game patterns may not be as relevant in discriminating efficacy as individual actions, and/or (ii) that the chosen variables were not sensitive enough to differentiate system dynamics. Overall, actions performed under non-ideal conditions were more central in most complexes, which suggests that playing off-system is the norm and should, perhaps, be considered as in-system! Thus, promoting tasks that stimulate playing under non-ideal conditions and expose the attackers to stressful conditions (e.g., cohesive blocks) may provide a greater transfer and ecological validity for training.

1. Introduction

The importance of identifying performance indicators lead researchers to apply Match Analysis (MA) in an attempt to enhance the coaches' knowledge and, consequently, the training process. Match Analysis may use a player-centred approach (Clemente et al., 2014; Sasaki et al., 2017) or a game-centred approach (Hurst et al., 2016; Loureiro et al., 2017). In latter sense, the interest in analysing relationships between game actions and their efficacy has increased (Mesquita et al., 2013; Silva, Marcelino, Lacerda, & João, 2016). The expectation is that such contributions may provide additional competitive advantage (Paulo, Zaal, Seifert, Fonseca, & Araújo, 2018). In this respect, there is a growing understanding that the game should be considered a functional whole, which has lead researchers to adopt systemic approaches that try to respect the complexity of the game (Lames & McGarry, 2007; Lebed, 2006; McGarry et al., 2002; Thelen, 2005). A systemic view of the functional relation between the game elements has thus emerged (Yamamoto & Yokoyama, 2011) and, in this context, Social Network Analysis (SNA) has provided valuable contributions for an increased understanding of the game complexity and dynamics (Passos et al., 2011; Ribeiro et al., 2017).

Social Network Analysis explores the interactions between agents to unfold meaningful, systemic relationships (L. Freeman, 2004; Quatman & Chelladurai, 2008). Largely based on Graph Theory (Wäsche et al., 2017), SNA provides a systematic understanding of the structure and dynamics of these elements (Boulding, 1956; Passos et al., 2011). In SNA, units of analysis are termed nodes, and usually correspond to agents (e.g., humans), while their relationships are expressed through lines connecting them (i.e., edges) (Wäsche et al., 2017). In the last decade, SNA has attracted interest in sports, as it uncovers networks of meaningful relationships between the players (Yamamoto & Yokoyama, 2011). Such player-centred approach has been quite frequent in sports (Clemente et al., 2014; Clemente, Martins, Kalamaras, et al., 2015; Sasaki et al., 2017), especially because SNA usually focus on agents. Nonetheless, we should remember that SNA is grounded on Graph Theory, meaning that nodes need not represent agents. In fact, game actions can be used as the functional units of analysis, being coded as nodes (Ortiz-Pelaez, Pfeiffer, Soares-Magalhaes, & Guitian, 2006). Such approaches have notably been applied in high-level volleyball (Hurst et al., 2017; Laporta, Afonso, & Mesquita, 2018a; Loureiro et al., 2017), and have established the possibility of using SNA within the context of game-centred researches.

Typically, SNA affords the application of centrality metrics, allowing researchers to evaluate the relative importance of each node within a given network (Sasaki et al., 2017; Zuo et al., 2011). However, many centrality metrics only consider the direct connections between nodes. In this context, Eigenvector Centrality may pose an advantage, as it weights both the direct and indirect connections between nodes, therefore providing a more comprehensive understanding of network dynamics factors (Bonacich, 1987, 2007; Ramos et al., 2017; Wasserman, 1994). Thus, this measure, by revealing the relative role of each node within the game dynamics, can provide the interconnectivity between game actions, for example in volleyball, the interaction between the Setting Conditions and the behavior of the actions occurred in the first and third contact (Hurst et al., 2016; Laporta, Afonso, & Mesquita, 2018b; Loureiro et al., 2017).

Recent researches in volleyball have successfully applied a number of relevant concepts: (i) using SNA within the context of a game-centred approached, i.e. considering game actions as nodes; (ii) pondering the direct and indirect connections through calculation of Eigenvector Centrality; and (iii) establishing comprehensive networks that consider the six functional game complexes (Afonso et al., 2017; Hurst et al., 2017; Hurst et al., 2016; Laporta et al., 2018a, 2018b; Loureiro et al., 2017). Notwithstanding, these researches have failed to address how such networks relate to or influence Play Efficacy, which refers to the effect obtained during each play or ball possession, and is therefore different of a rally; in volleyball, a rally is the entire point, encompassing all plays within that point dispute (Fédération Internationale de Volleyball, 2016).

In this study, SNA was applied to high-level volleyball matches, using a novel approach that expands upon previous research, and where very specific criteria were applied: (i) game actions were treated as nodes, and their connections as edges; (ii) Eigenvector Centrality was used to weight direct and indirect connections between nodes; (iii) Play Efficacy was evaluated, in order to afford the establishment of distinct networks or maps for each level of efficacy; and (iv) the game was coded according the well-established six functional game complexes, and each network considered all the complexes. The main goal is to understand if the type of network influences Play Efficacy.

2. Methods

Participants

A total of 1,618 actions (37 sets) from 9 matches of the 2015 men's World League Final Phase were analysed (teams: Brazil, USA, France, Poland, Italy and Serbia). There were 1,618 actions in K0, 1,615 in KI, 1,045 in KII, 408 in KIII, 125 in KIV, and 126 in KV. This study was approved by the Ethics Committee at the Centre of Research, Education, Innovation and Intervention in Sport of University of Porto (CEFADE 16.2017).

Measures

Figure 1 shows the six *Game Complexes* (K's) that were considered in the analysis (Hurst et al., 2017; Loureiro et al., 2017).

Fig 1:

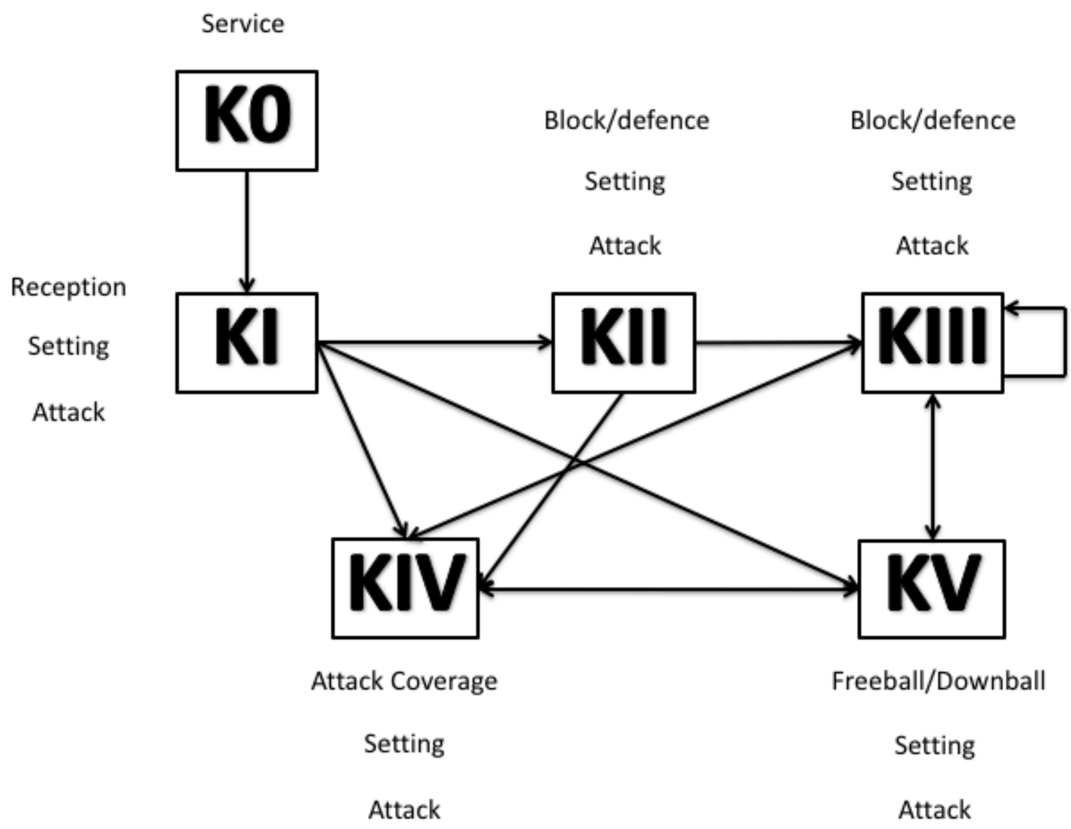

Fig 1. The six functional Game Complexes of volleyball.

The *Initial Position of the Server* consisted in server position (i.e., Zones 1, 6 or 5) (Quiroga et al., 2010). *Serve Type* was adapted from Costa, Afonso, Brant, and Mesquita (2012), and was divided into float jump serve (i.e., without ball rotation), jump serve (i.e., with ball rotation) and standing serve (i.e., without jumping).

The *Zone of First Contact* (reception or defence) followed the six official zones determined to the international rules established by the Fédération Internationale de Volley-Ball (FIVB). The additional category (Others Zone, OT) was added and corresponds to the outside court area (the athlete can recover the ball after the touch of the block or defence). *Setting Conditions* influence how many attackers are available to the setter: A - all attack options are available; B – quick attacks may still be deployed, but crossings between players are not possible; C – the setter can only use high sets (adapted from Laporta, Nikolaidis, Thomas, and Afonso (2015b); Rui Marcelino, Afonso, Moraes, and Mesquita (2014).

The *Attack Zone* consisted in the six official volleyball zones. *Attack tempo* denotes the synchronization between setter and attacker: (i) tempo 1 - attacker jumped before or at the same time as the set; (ii) tempo 2 – a two-step approach was performed by the attacker after the set; and (iii) tempo 3 - the attacker waited for the ball to ascend and then executed a three- or more-steps approach (adapted from Afonso and Mesquita (2007) and Costa et al. (2012)).

Block Opposition was adapted from Afonso and Mesquita (2011): (i) BO - no-block; (ii) B1 - individual block; (iii) B2 - double block; and (iv) B3 - triple block. *Available Players Before Attack Coverage* showed the available players to attack before of the attack coverage happened (adapted from Laporta, Nikolaidis, Thomas, and Afonso (2015a); Laporta et al. (2015b). The *Number of Coverage Lines* analysed the imaginary lines from the net until the endline, created by the players in the defence position at the moment of the opponents' attack.

Freeball represents the offensive organization after a ball that will have to be returned softly by the opponent, due to poor conditions for performing the third contact, while in the *Downball* the attacker was in an unfavourable condition to attack, but could still perform a standing spike (Hurst et al., 2017; Laporta et al., 2018a, 2018b; Loureiro et al., 2017). The *KV Target Zone* revealed where the KV ball landed (offensive or defensive zone).

Play Efficacy simply refers to the efficacy of each ball possession: (i) E0 - error; (ii) E1 - continuity of action; and (iii) E2 – scoring a point.

Design and Procedures

The matches were analysed directly from the websites *laola.tv* and *youtube.com,* having been recorded from a lateral view of the court (aligned with the net and with the camera moving to both sides), and were available in high definition (1080p). The data were registered in a worksheet created with Microsoft® Excel® 2017 (Microsoft Office Professional 365 Version 15.30, E.U.A). The macro function was used to instantly catalogue the codes into the appropriate cells.

Three observers with a Master's degree in volleyball and with an extensive experience as coaches (i.e., more than five years as coaches and with victories in national championships in their résumé) were trained in this instrument for a period of three months. During the process, two reliability tests were performed (the first after two months of testing the instrument, the second three months after that) to ensure consistency when applying the criteria and to provide the necessary adjustments in the variables and categories of the instrument. During these three months of training, weekly meetings were held for explanations and clarifications, discussion of emerging problems, as well as joint analysis of different matches (not used in the current investigation).

The first reliability test resulted from the analysis of 217 actions of a high-level men's match (qualification for the 2015 FIVB Volleyball World League, Pool E, 5 sets), of which four out of the 13 variables obtained Kappa values below 0.75. This originated a more in-depth discussion concerning those variables and their categories, which were redefined and improved to increase clarity and the likelihood of more homogeneous recordings.

After further training meetings (analysing both men's and women's matches), a second reliability testing of the instrument was performed, this time using a high-level women's match (play-off Match of the 2014/2015 Turkish Women's Volleyball League, totalizing 5 sets), with a total of 209 actions. While reliability of testing improved, one variable (*Type of Reception Line*) still presented values below the expected 0.75. Therefore, and after critical discussions, the researches decided to remove this variable from the study. The final analysis worksheet thus included the 12 variables described in Table 1.

Finally, the last test of data reliability was conducted with 415 actions of two randomly chosen matches of the Final Phase of the 2015 World League and Grand Prix, totalizing 10 sets. In this final test of the instrument, all variables presented Kappa values above 0.75, which is considered acceptable (Fleiss, Levin, & Paik, 2013). Only after this step was the instrument applied to the sample analysed in this manuscript.

Statistical Analysis

Data were examined using SPSS® for Mac (Version 22, IBM®, E.U.A.). A descriptive analysis was conducted to ensure data quality (i.e., verify input errors, data frequency and others). Secondly, Social Network Analysis techniques were applied using Gephi© 0.8.2-beta for Mac (Version 10.10.3, MacRoman, France). Nodes appeared in the periphery of the network so that all interactions could be clearly apparent. Nodes' size and colour were perfected to visually reflect the magnitude of their Eigenvector values. The nodes' size was stipulated between 500 (minimum) and 2,500 (maximum), and Eigenvector Centrality was used to identify the most influential nodes in the network. Edges were also depicted with a varying intensity in order to better reflect eigenvector values.

Regarding data reliability of the definitive data collection, the inter-observer reliability was calculated with the analysis of 10% of the total sample (total of 210 actions), as suggested in the literature Fleiss et al. (2013). Kappa values were above 0.75 for all variables.

3. Results

The network for Play Efficacy 0 is presented in Figure 2.

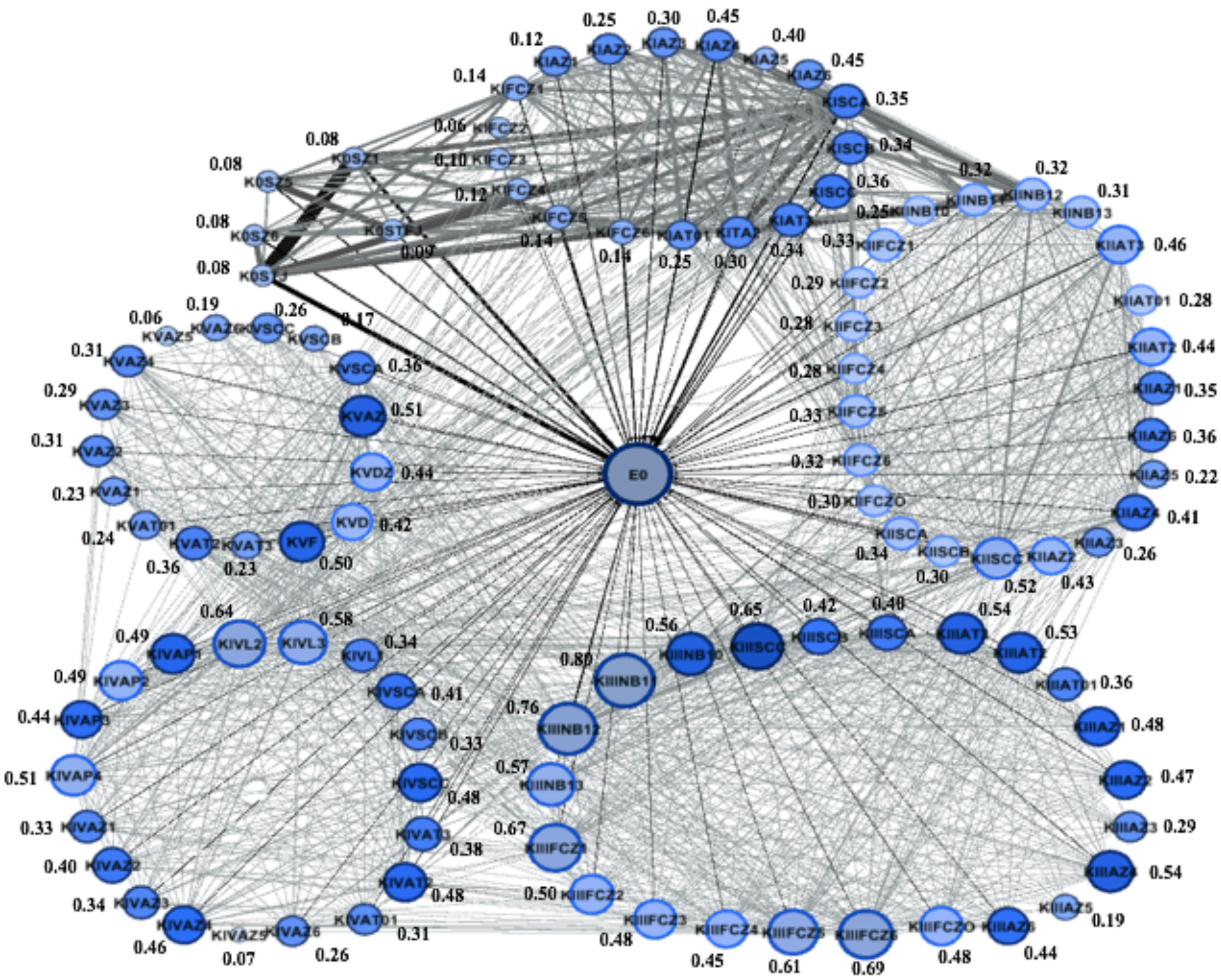

Fig 2. Network for Play Efficacy 0 (error).

Among the Eigenvector values for the network of Play Efficacy 0 (i.e., error), the categories with greatest centrality values were: (i) jump float serve (0.09) in K0; (ii) *Setting Condition* C in KI (0.36), KII (0.52), KIII (065), and KIV (0.48); *Setting Condition* A in KV (0.36); (iii) *Attack Zones* 4 and 2 in KI (0.30 and 0.39), KII (0.41 and 0.43), KIV (0.46 and 0.40), and KV (0.31 for both); *Attack Zones* 4 and 1 in KIII, (0.48 for both); (iv) *Attack Tempos* 2 and 3 in KI (0.30 and 0.34 respectively), KII (0.44 and 0.46), KIII (0.53 and 0.54), and KIV (0.48 and 0.38); *Attack Tempos* 2 (0.36) and 1 (0.24) in KV.

Figure 3 presents the network for Play Efficacy 1 (E1).

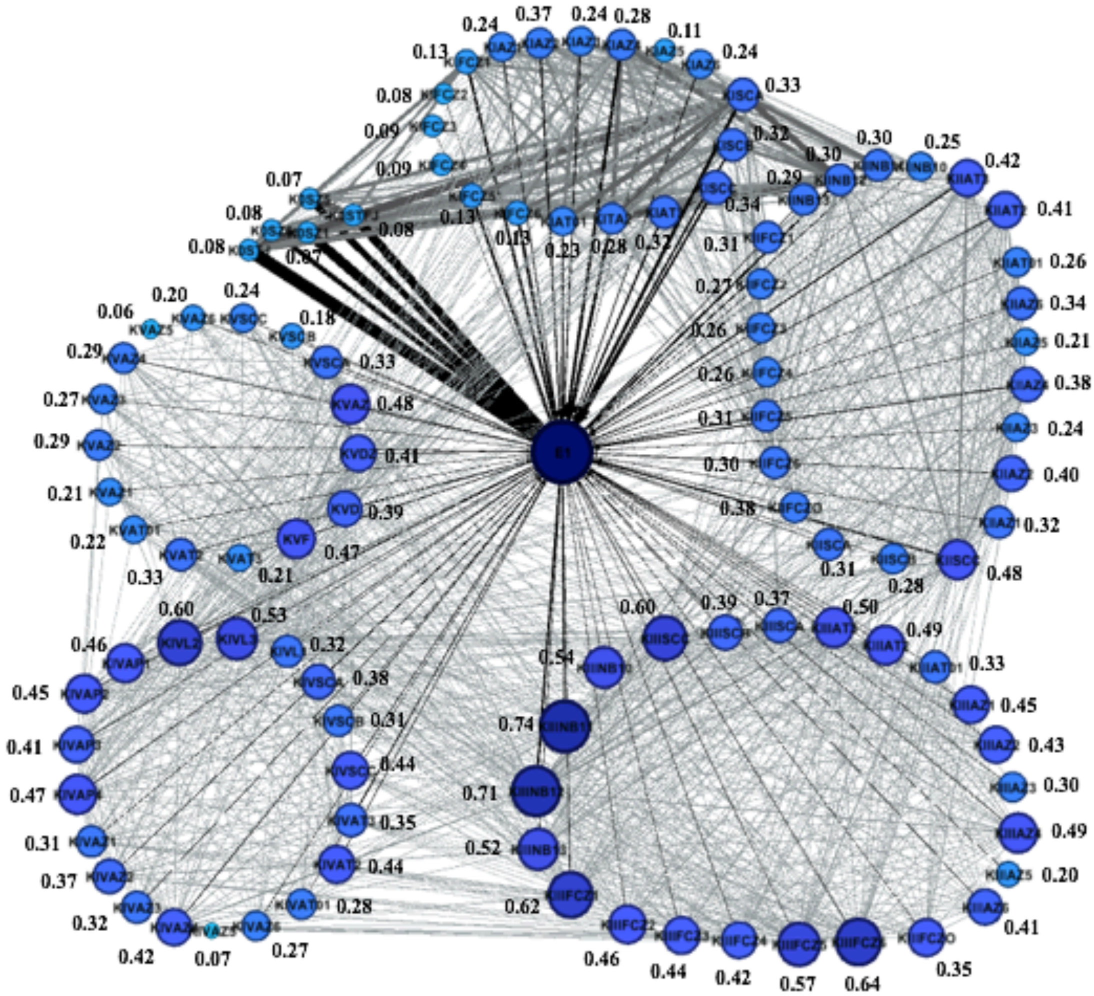

Fig 3. Network for Play Efficacy 1 (continuity).

For Play Efficacy 1 (i.e., continuity), the greatest centrality values were: (i) jump-float (0.08) and jump (0.08) serve in K0; (ii) *Setting Condition* C in KI (0.44), KII (0.48), KIII (0.60) and KIV (0.44); *Setting Condition* A in KV (0.33); (iii) *Attack Zone* 2 in KI (0.37), and KII (0.40); *Attack Zone* 4 in KIII (0.49) and KIV (0.42); *Attack Zones* 2 and 4 in KV (0.29 for both); (iv) *Attack Tempo* 3 in KI (0.32), KII (0.42), KIII (0.50), and KIV (0.50); *Attack Tempo* 2 in KV (0.45).

The network for Play Efficacy 2 (scoring a point) is presented in Figure 4.

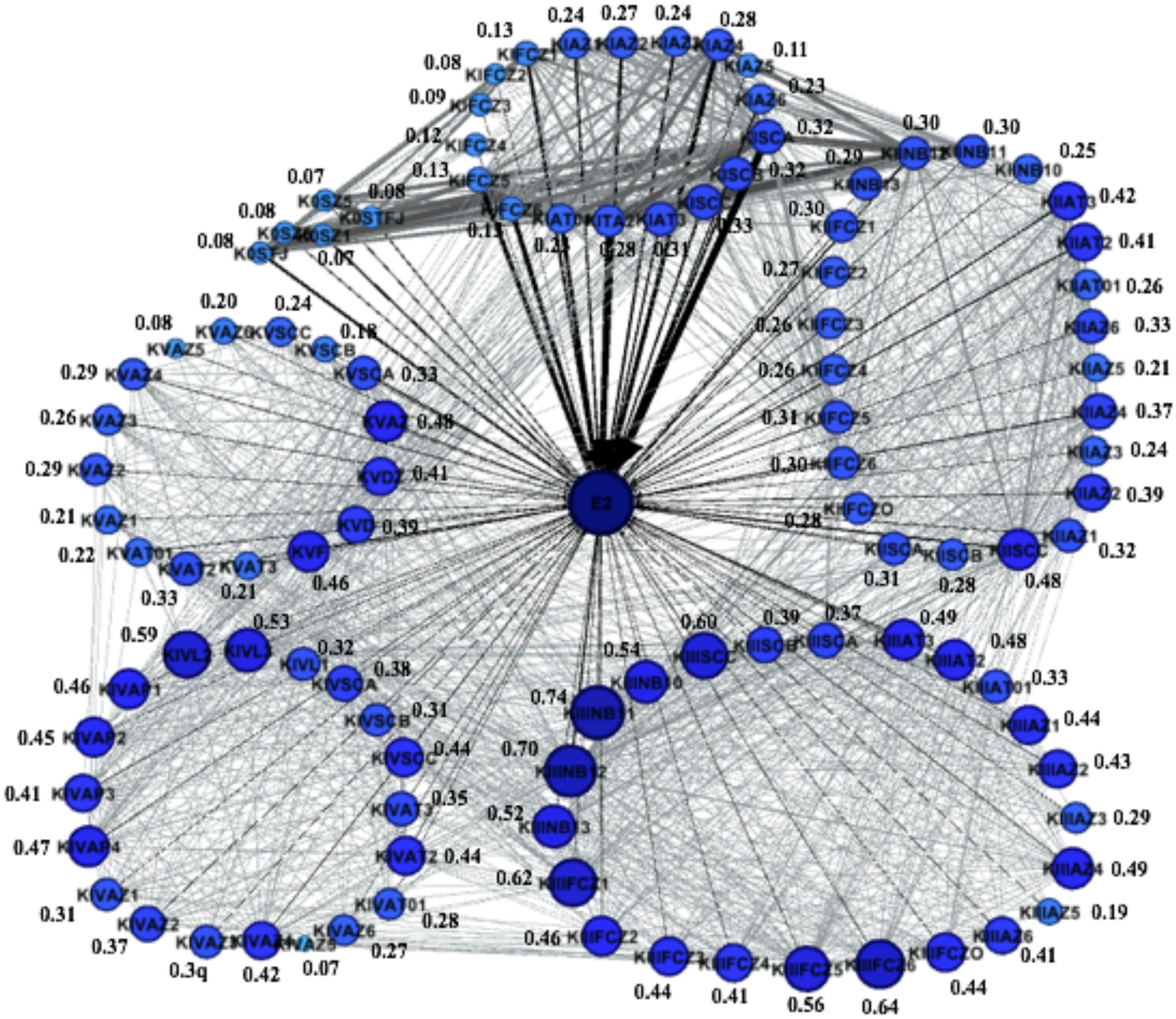

Fig 4. Network for Play Efficacy 2 (scoring a point).

In the network concerning Play Efficacy *2* (i.e., scoring point), the following centrality values were highlighted: (i) jump-serve and jump-float (0.08 for both) in K0; (ii) *Setting Condition* C in KI (0.33), KII (0.48), KIII (0.60) and KIV (0.44); *Setting Condition* A (0.33) in KV; (iii) *Attack Zones* 2 and 4 in KI (0.27 and 0.28 respectively), KII (0.39, 0.37), KIII (0.43, 0.49), and KIV (0.37, 0.42); *Attack Zone* 2 in KV (0.29); (iv) *Attack Tempo* 3 in KI (0.31), KII (0.42), KIII (0.49); *Attack Tempo* 2 in KIV (0.44) and KV (0.33).

4. Discussion

Match Analysis has developed methods for increasing our understanding of performance, and special attention has been devoted to establishing functional relations between game actions, as well as linking them with overall efficacy, in a game-centred approach. In this study, Social Network Analysis was used in order to explore the relationships between networks of game actions and Play Efficacy. Eigenvector Centrality was used considering the weight of the direct and indirect relations between game actions. Three distinct maps or networks were generated, one for each level of Play Efficacy (i.e., error, continuity, scoring a point). Altogether, these networks underlined the interconnectivity of all game actions and how they impact each other, and this was accomplished while respecting the existence of six functional and interdependent game complexes. However, and unlike our expectations, all three networks provided very similar structures and centrality values, exposing extreme similarities in game patterns, regardless of Play Efficacy.

All networks had one main aspect in common. The centrality values for non-ideal *Setting Conditions* (i.e., C) was a very noticeable result emerging from our data. Regardless of Play Efficacy, all networks presented game conditions that were far from the ideal conditions, and this occurred across every game complex, with the exception of KV (i.e., freeball), which is in accordance with previous studies (Hurst et al., 2017; Laporta et al., 2018a, 2018b). By definition, KV is expected to present reduced difficulties for playing the first contact which, in turn, is likely to generate better *Setting Conditions*. Previous studies have highlighted the need for coaches to develop off-system playing skills, since non-ideal setting conditions were more frequent than ideal setting conditions (Laporta et al., 2018a, 2018b). In this case, data is so clear that maybe an even stronger conclusion is warranted. Perhaps the concept of ideal Setting Conditions should be reformulated as a whole: if the most regular event is playing under far from ideal conditions, then what constitutes idealized conditions should be reframed. Space is a major constraint when preparing for performance (Jose Afonso, Francisca Esteves, Rui Araújo, Luke Thomas, & Isabel Mesquita, 2012), and our data suggests that this dimension should be approached differently than usual, e.g., non-ideal spatial conditions are actually the standard. This may also explain why this does not explain differences in Play Efficacy: over time, high-level teams have probably become comfortable and well-adjusted to playing under such constraints.

Another surprising result emerging from our data is the suggestion that predictable *Attack Zones* (i.e., zones 4 and 2, the extremities of the net) and *slower Attack Tempos* (i.e., tempos 2 and 3) are not actually impairing Play Efficacy. This result denotes that high-level volleyball matches have statistically predictable attack organizations. This predictability of space and tempo in attack is probably interconnected with the clear centrality of non-ideal *Setting Conditions*. Team sports should provide a balance between predictability and uncertainty (Lames & McGarry, 2007), i.e., deliver a solid structure, but also encompass a degree of necessary uncertainty to surprise the opponent. Our data suggests that high-level men's volleyball is pending perhaps a bit much towards the predictability side, and thus game patterns are becoming too stereotyped. On the positive side, this may suggest a greater role for individual technique and decision-making to unbalance the opponent (Afonso & Mesquita, 2011; Mesquita & Graça, 2002; Queiroga, Matias, Greco, Graça, & Mesquita, 2005).

Overall, the three networks were not sufficiently sensitive to determine the three levels of Play Efficacy. Game patterns were highly similar across all three levels, meaning that future studies should probably use more refined variables and/or categories. The differences emerging in the present study were minor and consisted of almost insignificant variations of similar themes. However, it is also possible that the explanation for differences in efficacy are not related with game patterns, but with individual actions, which would require a very different approach in terms of selected variables. Afonso and Mesquita (2011) found similar results when analysing the variables that influence the *Attack Efficacy* and *Block Cohesion* in Women's volleyball. In particular, the authors noted that *Block Cohesion* had no influence on *Attack Efficacy.* In other words, the authors suggested that the individual skill and the privilege of the attacker contacting the ball before the defender may overcome the importance of how the play was previously developed.

In any of the previously mentioned cases, it would be important for teams to promote representative tasks and ecological validity through: (i) regularly creating training scenarios that demand playing under non-ideal *Setting Conditions*; (ii) attempting to increase unpredictability even under such conditions; (iii) preparing the individual athlete to attack under very stressful conditions, especially with cohesive blocks performed by two or three players. Future research should review of what is considered as the ideal *Setting Conditions*, as well as applying a mixed approach where both collective and individual variables are collected, providing an analysis that is potentially more sensitive and discriminating, and therefore more closely associated with a given outcome of Play Efficacy.

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IV. Considerações Finais

Considerações Finais

A presente tese examinou a potencialidade e a contribuição da utilização da ARS no estudo dos JD, através de uma análise global e sistémica (i.e., considerando todos os complexos de jogo de suas interações), pela consideração das ações de jogo enquanto unidades de análise (i.e., nós) e aplicação da Centralidade de Autovetor (i.e., pesando tanto as conexões diretas quanto indiretas). Ademais, dois dos artigos visaram analisar a relação destes fatores com a eficácia das jogadas, tendo-se criado redes ou mapas específicos para cada nível de eficácia. Acreditamos ter gerado contributos relevantes em diferentes domínios.

Unidades de análise (nós) não-agenciais

Estudos envolvendo a AJ e a busca por indicadores de desempenho que respeitem a ecologia do jogo, têm vindo a utilizar métodos de análises sistémicos respeitadores da complexidade dos JD (Paulo, Zaal, Seifert, Fonseca, & Araújo, 2018). A ARS, ao verificar padrões de comportamento, estrutura e dinâmica da interação entre as unidades de um sistema (Freeman, 2004; Wasserman & Faust, 1994), fornece uma visão global do jogo evitando negligenciar as partes (Passos et al., 2011).

Apesar da maioria das pesquisas nos JD utilizarem uma abordagem centrada na interação dos jogadores como unidades de análise (Clemente et al., 2016; Duch et al., 2010; Ribeiro et al., 2017; Wäsche et al., 2017), a definição de elementos e relações a serem estabelecidas dependem da questão a ser pesquisada assumindo diferentes tipologias (atletas, propriedades, animais, ações de jogo) (Ortiz-Pelaez et al., 2006).

Neste sentido, notámos que as raízes matemáticas da ARS permitem uma abordagem centrada no jogo utilizando ações de jogo para revelar diferentes padrões de interação. Alguns autores deram os primeiros passos nesta abordagem e utilizaram a interação entre ações de jogo pertencentes a alguns Complexos de Jogo no voleibol de alto nível (Hurst et al., 2017; Hurst et al., 2016;

Loureiro et al., 2017). Apesar destes estudos não considerarem o jogo na sua totalidade (dois estudos analisaram a interação entre os Complexos I, II e III, e o outro a interação entre o Complexo IV e V), foi possível identificar a importância e o comportamento de algumas variáveis nestes momentos de jogo.

Assim sendo, a utilização de uma abordagem centrada no jogo através das ações de jogo, pode ser uma via para fornecer informações para sustentar a potencialidade da interconectividade de unidades não-agenciais e respeitar a ecologia do jogo. Entretanto, expandimos esta abordagem e, através da análise da interação entre os seis Complexos de Jogo tanto no voleibol feminino quanto no masculino, alcançamos um olhar verdadeiramente sistémico, revelando o comportamento das variáveis em todas situações de jogo.

Relevância da centralidade de autovetor para uma análise sistémica

Ao utilizar uma abordagem centrada no jogo, recorremos a Centralidade de Autovetor, a qual fornece a importância de um agente no sistema, levando em conta os pesos atribuídos às ligações diretas e indiretas entre os outros nós (Bonacich, 1987, 2007; Borgatti, 2005), para assim, alcançar a ecologia do jogo através da interação entre as ações de jogo em todos os seis Complexos de Jogo.

Apesar desta medida ser pouco utilizada nos JD, o primeiro e o segundo artigo empírico revelaram a complexidade e dinâmica do funcionamento das ações de jogo dentro de cada momento do jogo. Esta medida de centralidade revelou o papel relativo de cada nó, fornecendo uma perspetiva mais aprofundada dos fenómenos decorrentes na relação global entre as ações de jogo; como por exemplo, o comportamento e a ligação das ações de segundo toque com as ocorridas no primeiro e terceiro toque no voleibol.

Neste sentido, os resultados descortinaram as diferenças e semelhanças dos padrões de interação entre as ações de jogo em cada Complexo de Jogo. Algumas ações se evidenciaram e afetaram a dinâmica do jogo apresentando um comportamento comum de jogar fora do sistema na maioria dos Complexos de Jogo; ou seja, algumas ações foram desenvolvidas em condições não-ideais de jogo (por exemplo, nas piores Condições de Distribuição, com Tempo de

Ataque lentos e pela utilização de Zonas de Ataque localizadas nas extremidades da rede).

A utilização desta ferramenta permitiu, ainda, evidenciar ama forte relação entre os Complexos de Jogo, onde os que ocorriam antes ou depois produzem forte impacto nas ações de jogo subsequente. A título de exemplo, as ações de jogo do Complexo II com as do Complexo III; onde, uma maior imprevisibilidade no KII (com diversificada Zonas e Tempos de Ataque) dificultou e restringiu as ações no Complexo III tornando-o mais previsível (com tempos de ataque mais lentos e com menos zonas de ataques). Apenas o KV apresentou melhores condições com valores mais elevados de autovetor, com uma distribuição mais uniforme para as diferentes Zonas de Ataque da linha de frente da rede (Zona 2, 3 e 4) e Tempos de Ataque mais rápidos (Tempos 1 e 2), o que comprometeu a ação do bloco adversário, evidenciado através dos valores elevados de blocos simples e duplos no KIII.

Em suma, a Centralidade de Autovetor, através das ligações diretas e indiretas, evidencia uma visão ecológica do jogo, porquanto identifica as especificidades de ocorrência e a influência de cada ação dentro do jogo de voleibol. Além disso, os resultados exibiram padrões de comportamentos das variaveis que auxiliarão na otimização do processo de treino. Apesar de frequentemente o treino ser desenvolvido englobando ações em condições ideais, o presente estudo sugere que as situações “fora do sistema” devem ser consideradas no planeamento do treino, tendo em vista o seu papel central na maioria dos Complexos de Jogo.

Eficácia das jogadas e a necessidade de redes diferenciadas

Através da observação dos resultados encontrados, o próximo passo desta dissertação foi dado, na tentativa de sondar se estes padrões de comportamento influenciavam a eficácia final das ações, tanto no voleibol feminino como no masculino de alto nível. Assim, o terceiro e o quarto artigo empírico ampliaram a utilização da ARS e da Centralidade de Autovetor no voleibol feminino e masculino, afim de entender como os padrões de jogo dos seis Complexos de Jogo impactariam na eficácia final de cada ação de jogo. Os padrões de jogo foram relacionados a níveis distintos de Eficácia (E0 – Erro, E1 – Continuidade da ação e E2 - ponto), proporcionando uma rede para cada eficácia.

Embora a visão predominante seja a de que os distintos padrões de jogo afetam a eficácia (Afonso, Mesquita, & Coutinho, 2008; Marcelino, Mesquita, & Afonso, 2008), existem resultados dissonantes na literatura sugerindo que talvez a habilidade individual (e não os padrões de jogo) seja mais determinante para a eficácia (por exemplo Afonso and Mesquita, 2011; Mesquita and Graça, 2002). No nosso estudo, as variáveis analisadas expuseram a mesmo tendência porquanto, os padrões de jogo foram semelhantes para os três níveis de eficácia considerados. Estes resultados estão de acordo com estudos anteriores no voleibol feminino (Afonso & Mesquita, 2007; Afonso, Mesquita, & Marcelino, 2008), evidenciando que as habilidades técnico-táticas individuais são os fatores que, provavelmente, mais interferem na eficácia no jogo. Cabe destacar que poucas variáveis mostraram resultados distintos entre os três níveis de eficácia indicando mais uma resposta aleatória do que um padrão de jogo confiável, como é o caso da Zona de Serviço 6 no feminino, em que a mesma apresentou maior valor de centralidade relacionada ao Erro (E0) do que a continuidade (E1) e ao Ponto (E2), e ainda, no masculino, a Zona de Serviço 1 e 5 no K0 relacionado à E0 foram diferentes da relacionada à E1 e E2.

Portanto, a habilidade individual do atacante e o facto do mesmo estar numa situação de “posse de bola”, pode ser mais preponderante para determinar a eficácia, do que o desenvolvimento de cada *rally* (Afonso & Mesquita, 2007; Afonso, Mesquita, & Marcelino, 2008, Mesquita & Graça, 2002; Queiroga et al., 2005). Os nossos resultados evidenciam a importância de se considerar aspetos de desempenho individual dos jogadores para determinar a eficácia no momento do ataque no voleibol feminino de alto nível.

Estes estudos, evidenciaram que os treinadores devem promover tarefas com uma maior validade ecológica, criando situações de treino que incrementem a versatilidade técnico-tática dos jogadores para atuarem em piores condições de jogo (como, por exemplo, piores condições de distribuição e com blocos coesos).

Síntese global

No geral, a presente tese evidenciou o poder da ARS e a sua contribuição para entender a ecologia, a dinâmica do jogo e aceder a uma visão sistémica do voleibol. A utilização de uma abordagem centrada no jogo recorrendo às unidades de análise não-agenciais (ações de jogo), evidenciou ser um caminho profícuo para a identificação de novos padrões de jogo. Alguns padrões das variáveis de jogo revelaram comportamentos interessantes a respeito da dinâmica e ecologia da interação entre os seis Complexos de Jogo analisados, como por exemplo, o jogo "fora do sistema" em algumas variáveis. Além disso, embora a tendência da investigação seja que os padrões de jogo afetam na eficácia das ações, sugere-se que a habilidade individual dos atletas deve ser um fator relevante a se considerar para a eficácia de cada momento de jogo.

A Centralidade de Autovetor, ao considerar as ligações diretas e indiretas de cada agente na rede, evidenciou ser um importante instrumento na medida em que proporciona informações a respeito do papel relativo de cada nó dentro do sistema (Bonacich, 1987, 2007; Bonacich & Lloyd, 2001; Borgatti, 2005). Assim, ao considerar as ações de jogo e os seus papéis relativos em cada complexo do jogo, além de se obter um resultado mais refinado, o presente estudo revelou comportamentos interessantes de algumas variáveis (como por exemplo, Condições de jogo não-ideais), e como estes comportamentos influenciam a eficácia final das ações.

Desta forma, os resultados do presente estudo devem ser considerados e servir de reflexão para a melhoria do processo de treino, e, até mesmo, ocupar um papel preponderante no planeamento das situações no treino. As situações "fora do sistema" devem ser treinadas como regularidades no treino, de modo a preparar os jogadores para enfrentarem situações que ocorrem com elevada dificuldade, especialmente no treino das ações individuais de ataque sob diversos tipos de situações; como por exemplo, na presença de blocos coesos de dois e três jogadores, com a presença de poucas opções de ataque e com Tempos de Ataque lentos.

Entendemos que este tipo de abordagem é relativamente recente na investigação da AJ no voleibol e que ela possui limitações a serem trabalhadas. Neste sentido, futuros estudos podem mostrar novos caminhos para abrir outras possibilidades de análise e melhorar o entendimento da dinâmica do jogo. A título de exemplo, revela-se interessante avaliar se as restrições situacionais impactariam nas ações individuais (como por exemplo, o momento do jogo, o *status* da partida, o tipo de jogo, vantagem casa); o comportamento das variáveis não-agenciais utilizando diferentes medidas de centralidade; associar a posição/especialização funcional/características do jogador e a eficácia final das ações; como ainda, replicar o estudo em diferentes níveis de jogo e competição para entender se estes resultados constituem uma características do voleibol atual, ou somente da amostra selecionada, isto é, o nível de rendimento mais elevado.

V. Referências

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