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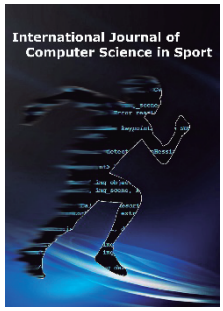

A scoping review using social network analysis techniques to summarise the prevalence of methods used to acquire data for athlete surveillance in sport

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Abstract

To aid the implementation of athlete surveillance systems relative to logistical circumstances, easy-to-access information that summarises the extent to which methods of acquiring data are used in practice to monitor athletes is required. In this scoping review, Social Network Analysis and Mining (SNAM) techniques were used to summarise and identify the most prevalent combinations of methods used to monitor athletes in research studying team, individual, field- and court-based sports (357 articles; SPORTDiscus, MEDLINE, CINHAL, and WebOfScience; 2014-2018 inc.) . The most prevalent combination in team and field-based sports were HR and/or sRPE (internal) and GPS, whereas in individual and court-based sports, internal methods (e.g., HR and sRPE) were most prevalent. In court-based sports, where external methods were occasionally collected in combination with internal methods of acquiring data, the use of accelerometers or inertial measuring units (ACC/IMU) were most prevalent. Whilst individual and court-based sports are less researched, this SNAM-based summary reveals that court-based sports may lead the way in using ACC/IMU to monitor athletes. Questionnaires and self-reported methods of acquiring data are common in all categories of sport. This scoping review provides coaches, sport-scientists and researchers with a data-driven visual resource to aid the selection of methods of acquiring data from athletes in all categories of sport relative to logistical circumstances. A guide on how to practically implement a surveillance system based on the visual summaries provided herein, is also presented.

KEYWORDS: TRAINING LOAD, ATHLETE MONITORING, ACCELEROMETRY, CENTRALITY, FIEDLER VECTOR

Introduction

Establishing athlete surveillance systems to regularly monitor training stimuli and responses to training in all sports is encouraged not only to improve performance but often with an ambition or expectation of being able to better manage training loads to reduce the risk of injury or illness (Drew et al., 2016; Schwellnus et al., 2016; Soligard et al., 2016; Williams et al., 2016; Bourdon et al., 2017; Campbell et al., 2017; Sands et al., 2017). A large number of methods are available to enable players, coaches, sport scientists and medical staff to acquire data from athletes. To provide a more complete understanding of the training load dose-response effect on athletes, it is recommended that the combination of methods selected to monitor athletes should enable external (e.g., work done/mechanical load) and internal (e.g., physiological and psychological responses) measures of training load to be derived (Soligard et al., 2016; Bourdon et al., 2017; Impellizzeri et al., 2019). To understand the relevance of training load measures to a particular type of sport, readers are encouraged to directly appraise evidence validating their use in that sport and their relationship with a desired outcome (e.g., performance/injury; Impellizzeri et al., 2020b). To help prioritise the practical implementation of athlete surveillance and decide which combination of monitoring approaches to employ, a list of the strengths and limitations (e.g., cost, additional hardware/software needed, ease of use etc.) for individual methods of acquiring data have been published (e.g., Bourdon et al., 2017). These methods have also been classified based on the external and internal measures of load they provide (Bourdon et al., 2017). Whilst a list of strengths and limitations for each method of acquiring data is informative, at present, there is no easy-to-access information that indicates which methods are typically used alongside others in order to help meet recommendations to use external and internal methods of acquiring data to monitor athletes. In addition to a list of strengths and limitations, a summary of the range and extent to which methods are used in combination with other methods to monitor athletes in practice, would provide additional information to help coaches select methods and implement athlete surveillance systems across different types of sport.

In addition to a list of strengths and limitations for each method, a summary of the range and extent to which methods are used in combination with other methods to monitor athletes in practice may also help those responsible for implementing surveillance systems select methods that match their practical, logistical and contextual circumstances to make sure that data is easy to collect, analyse and interpret based on funding, expertise and time available (Soligard et al., 2016; Bourdon et al., 2017; Campbell et al., 2017). For instance, a method that has the highest number of strengths and the least number of limitations, is not necessarily 'the best' method to use in practice if there is insufficient financial and logistical support to implement it on a consistent basis. Bourdon and colleagues (2017) support this by suggesting that even a method with some limitations could provide information of sufficient meaning to influence practice if it is used consistently over an extended period of time (Bourdon et al., 2017). In less well-resourced or smaller operations, knowledge of the extent (i.e., prevalence) to which methods or different combinations of external and internal methods are used to acquire data from athletes, could be used to help select slightly less prevalent methods, but ones that better match the available resources and can be used consistently over time to provide valuable feedback.

Summarising methods used to acquire data from athletes may also help those responsible for implementing surveillance systems to learn from and be informed by the selection of methods used in similar sports and possibly in different sports, to select combinations of external and internal methods that also match logistical circumstances. A clear and detailed picture of the prevalence of different combinations of methods used to acquire data in different categories of sport would also provide an opportunity to identify gaps in knowledge, allowing comparison

of the methods used across different categories of sport, to highlight whether the approaches taken in one category of sport are similar or dissimilar to another.

Whilst obtaining data about methods used directly from those responsible for implementing athlete surveillance systems could provide the strongest indication of methods used in practice, attaining representative information across a number of different sports is likely heavily influenced by researcher contacts and response bias. Although not a direct reflection of methods used by coaches in practice, summarising methods used to monitor athletes in published research would still provide a clear indication of the range and combination of external and internal methods used in different types of sport to monitor athletes.

A scoping review provides an opportunity to synthesise a large and diverse body of literature on a topic that has not been extensively reviewed or at first glance, appears to be complex in nature (Arksey & O'Malley, 2005). However, traditional methods for compiling a narrative synthesis and summarising a body of literature of this size and diversity could present more challenges than it would solve. A narrative synthesis might also make it difficult for coaches, researchers and practitioners to 'see' and use the information to inform decision-making, which could limit the effectiveness of the review. The application of novel, contemporary data-driven methods that enable the range and extent of different combinations of methods used to acquire data from athletes in different categories of sport to be visually mapped and the most prevalent combinations of methods to be identified, is therefore appealing.

In data science, *graph theory* is a data-driven approach that can visually model and elucidate the relationship between a pair of objects or units of interest (nodes). It has particularly come to prominence within Social Network Analysis and Mining (SNAM; Santos & Lopez., 2019) which is applied to visually present and further analyse large and complicated connections between individuals (nodes) such as those found in social media (Facebook, Twitter, etc.). Using SNAM techniques, large complex datasets can be graphed (sometimes referred to as a sociogram, network plot or graph) to clearly display the most prevalent nodes or groups of nodes in a network (Leppink & Pérez-Fuster., 2019). Visual information to quantify the strength of any connections or links between nodes can also be presented in a network. Furthermore, the central or outer positioning of nodes in relation to other nodes in the network can be objectively quantified using additional measures (e.g., via centrality measures; CMs), to sort nodes in order of their popularity, or in this case, prevalence within the network, based on how connected a method (node) is to other methods (nodes). Instead of counting the number of times a method is independently used to inform a narrative synthesis in a review (i.e. vote counting), the use of SNAM appears to provide an efficient and attractive approach for collating, summarising and visually presenting insightful information, in this case, about the range and extent of different combinations of methods used to monitor athletes from a large and diverse body of literature (Santos & Lopez., 2019).

In addition to vote counting, this scoping review therefore uses SNAM-based visual and quantitative analyses to provide a clear and concise snapshot of methods and combinations of methods used to acquire data from athletes in published research across different categories of sport (team vs individual; field-based vs court-based sports) during a five-year publication period (2014-2018). In the process of achieving this, this review also specifically aims to: 1) identify and compare the most prevalent combinations of external and internal methods of acquiring data in each category of sport; 2) identify gaps in the literature where certain categories of sport may be less well researched; and 3) based on differences or similarities in methods used in each category of sport, identify opportunities for certain categories of sport to learn from the monitoring approaches used in another category.

Methods

This scoping review follows the stages outlined by Arksey & O'Malley (2005) and uses a systematic methodology to identify and select relevant articles, extract data and collate, summarise and report the results.

Identifying relevant articles

In accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses Extension for Scoping Reviews (PRISMA-ScR; Tricco et al., 2018), a Boolean search phrase containing terms relevant to the population (e.g., athlete or player), intervention/exposure (e.g., training load), comparator (e.g., match or training) and outcome (e.g., injury or performance; PI/ECO) was applied across the four electronic databases of MEDLINE, SPORTSDiscus, CINHAL, and Web of Science Core[1]. Relevant keywords were determined through a search of titles, keywords, abstracts and full texts of existing articles known to the authors. A total of 4524 articles were identified across all four databases and citations were imported into the Mendeley Reference Manager (Mendeley Desktop v1.19.4). After removal of duplicates, 2734 were identified for screening (Figure 1).

Inclusion/Exclusion Criteria

A pilot screening of 34 articles (published in 2014) was undertaken by the authors to increase familiarity with the literature and following an iterative process, a final list of the inclusion and exclusion criteria was devised and applied by Author 1 to all articles (Figure 1). A two-phase screening process consisting of title and abstract (phase-one) and full-text (phase-two) screening was then employed and 357 articles were selected for inclusion in the review. If it was not clear whether to accept or reject an article based on title and abstract screening, then the full-text article was reviewed.

In summary, articles were eligible for final review if they described objective or subjective methods of acquiring data from athletes relevant to performance or injury outcomes. To maintain the focus on methods of acquiring data for 'in-the-field' surveillance of athletes, articles that described the monitoring of athletes only during laboratory assessments, were omitted. Articles were also excluded if they focused on monitoring athletes for a specific type or site of injury (e.g., ACL, tennis elbow, etc.) to avoid biasing the results based on specialised or injury-specific methods used to monitor these athletes.

Data Extraction

From each article included in the review, the following data were extracted and recorded; title, author(s), year of publication, sport, aim of the paper, participant details (sample size, age, gender, competition level), reasons for monitoring (prospective monitoring, performance or injury) and the methods used for acquiring data.

Similar to the methods listed by Soligard et al. (2016), Bourdon et al., (2017) and Newton et al. (2019), a total of seventeen methods of acquiring data were identified. As labelled by Bourdon et al., (2017), the *internal* methods identified were: Rating of Perceived Exertion (RPE), Session Rating of Perceived Exertion (sRPE), Heart Rate (HR), Maximal Oxygen

[1] Employing a combination of 'AND/OR' operands, the following search was entered ((athlete* OR player* OR elite OR runner* OR novice* OR amateur* OR professional* OR athlete*) AND (training load*, workload*, PlayerLoad*, dose*, volume*) AND (training OR session* OR season* OR match* OR competition*) AND (injury* OR performance*)) – ENGLISH Language articles only between January 2014 and October 2018.

Update (VO2), Blood Markers (BloodMarkers), Questionnaires, Self-Reported Training (SelfReport) and Energy Expenditure (EE). The *external* methods identified were: Global Positioning Systems (GPS), Accelerometer/Inertial Measurement Units (ACC/IMU), Video, Time Motion Systems (TM), Frequency/Count (Freq.Count), Duration, Volume/Distance (VolumeDistance), Power Output (PowerOutput) and Metabolic Power (Met.Power). While a number of monitoring methods (e.g., GPS, ACC/IMU, HR) used to acquire data can also provide a measure of duration, 'Duration' (e.g., length of a session or minutes played) was only counted as an independent method of data acquisition where it was listed as a primary (unspecified) method in the research article. Distance prescribed in a training programme or acquired using an unspecified method (i.e., not a GPS device) was classified as 'VolumeDistance'. In articles where data was acquired using an integrated device (e.g., GPS device by Catapult Innovations, Melbourne, Australia), as not all components available from these devices were used in the article, only the individual components reported and used were recorded (i.e., HR, GPS, ACC/IMU). Whilst a method used to acquire data, RPE also provides a unit of measure for monitoring internal training load and technically, since sRPE is further derived from RPE, it is also a measure of training load. In this analysis however, we have included sRPE as a separate method of acquiring data (Halson, 2014) as it only takes a small adjustment to turn RPE into sRPEs (RPE x session duration) and we therefore suspect sRPE is likely to have been recorded directly during monitoring. Separating these methods allows the popularity of using sRPE over RPE to also be seen (Haddad et al., 2017).

For each article, methods of acquiring data were reported as either a one (true) or a zero (false) and resulted in a matrix (*columns*: n=17; *rows*: n=357) consisting of ones and zeros. This matrix formed the basis for applying SNAM-based techniques to describe the level of interaction between nodes, or in this case the number of times individual methods of acquiring data were collected in combination with other methods in the same article. The number of times separate methods of acquiring data were used together in the same article was used to quantify the strength of connection between the combination of methods used in articles overall. This meant the strength of a connection between methods increased as subsequent articles using the same combination of any two methods or more added to the size of these links. The overall strength of connections between methods, therefore represented a 'count' for the number of times methods appeared together in articles (number of connections between pairs of methods summed across articles) and was interpreted, for the purposes of this review, as the prevalence with which different combinations of methods of acquiring data were used in practice.

Collating, summarising and reporting the results

Bubble plots (see Figure 3) displaying the proportion of each method of acquiring data used within articles from each year between 2014-2018 and by category of sport (i.e., team, individual, field-based, court-based) were used to provide a simple numerical summary of the trends and gaps in the methods used across years. In addition, the standard deviation of the proportion of each method of acquiring data, was calculated to indicate how consistent the relative use of a method was in proportion to other methods used across years. To enhance a comparison of the relative prevalence of methods of acquiring data between different types of sport, the standard deviation as a measure consistency was used to order the methods displayed in the bubble plots. If the relative use of a method was more consistent across years, it was positioned more towards to left and if the relative used of a method was less consistent across years, it was positioned towards the right.

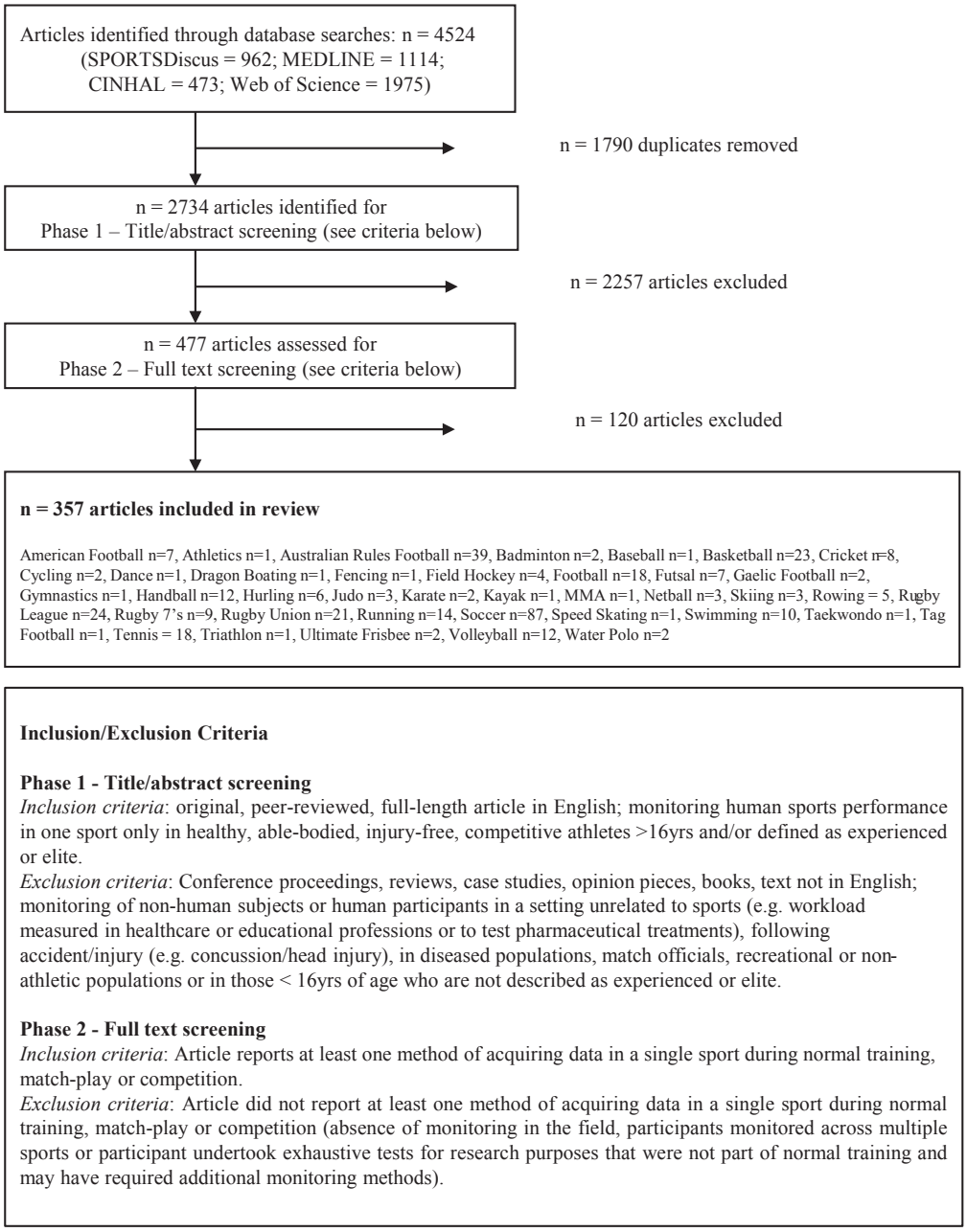


Figure 1. PRISMA-ScR flowchart of the article selection process including inclusion and exclusion criteria.

Social network analysis and mining (SNAM)

Network Plots

A social network is a constellation of nodes and links (Himelboim, 2017). A *node* (also known as a *vertex*) is used to represent a unit of interest, for example, a user (i.e., Facebook or Twitter) or in this case a method of acquiring data. A *link* (or *edge*) is used to describe a *connection* between two nodes, for example, a 'friendship' between two Facebook users or in this case, to indicate the number of times a pair or multiple methods of acquiring data were used in a single paper. A *graph* (G), therefore presents a model of nodes and links to capture and quantify the

strength of relationships between nodes. Consequently, links between nodes can have a *weight* which indicates the strength (or some other attribute) of each connection between the nodes.

Undirected, directed and multi are all types of graphs that describe the direction of the links between nodes. Undirected graphs have links that *do not* have a direction and therefore indicate a two-way relationship (link can be traversed in both directions) between nodes. Directed graphs have links that *do* have a direction and indicate a one-way relationship between nodes. Multigraphs demonstrate multiple links with the same source and target node(s). The type of graphs displaying methods of acquiring data extracted in this review (summed across all years) used undirected, weighted multigraphs (see Figure 2).

The methods of acquiring data were converted into an adjacency matrix (A), where A is a *square* matrix with a value of zero corresponding to no link between two nodes, non-zero entries representing a link between two nodes and the value of the entry (weight of the link/thickness of the line) indicating the number of times a pair or combination of methods including that pair were used in the same paper. If a link exists, then the nodes are considered to be adjacent.

Global graphs representing methods of acquiring data across all years were created by applying a force-directed algorithm (Fruchterman & Reingold, 1991) that treated links like springs and holds nodes with a high link weight closer together whilst treating nodes with a low link weight as repelling objects. Simulation continued until the positions of the nodes were close to an equilibrium with node(s) with the strongest links taking up a central prominent position in the graph. It is important to note that the location of the nodes exist in a multidimensional space rather than two-dimensionally as they are displayed on the page. Node sizes were normalised so that comparisons between the prevalence of methods used to acquire data across different categories of sport could be seen. Different colours are used in network graphs to identify methods of acquiring internal (red) and external (yellow) data.

The *size* of the graph can be defined as the total number of nodes present in a network whilst the *density* of a graph is defined as the proportion of actual links between the nodes relative to the potential number (total) of links that could exist in a fully connected graph. These two heuristics give a basic overview of the arrangement (topology) of the network(s) and help to quantify whether: 1) a single or a group of nodes are dominant; (2) links between nodes are sparse and therefore no particular hierarchy between methods exists (low density); or (3) nodes are of a similar status and prominence within the network (high density).

Centrality Measures

In addition to the visual representation of methods used to acquire data shown in graphs (see Figures 4 & 5), a large part of applying SNAM-based techniques is to quantify the position of each node and the relationship with and between other nodes. Centrality measures (CM) are heuristics used to measure the distance between nodes in a network and quantify how central, important or in this case, how prevalent different combinations of nodes are in a network. The use of CMs to objectively quantify importance and order nodes (methods of acquiring data) by focuses on identifying three features: (1) how 'active' a node is within the network, i.e., whether it maintains many links with other nodes; (2) the physical location of a node alongside other nodes in the network, i.e., how short the distances are between nodes; and (3) whether a node lies on many paths between different nodes in the network (Freeman, 1977). Whilst there are many different measures that can be used to quantify centrality, this scoping review focuses on adopting four commonly used CMs – degree (D; Freeman, 1979), closeness (C; Sabidussi, 1966), betweenness (B; Freeman, 1979) and eigenvector centrality (E; Bonacich, 1972). These heuristics summarised in Table 1., present different novel ways to quantify the position and

importance of each method based on how connected it is. The level of connectedness that each method has is then used to quantify in practice, how prevalent that method of acquiring data is in relation to other methods.

Table 1. Centrality measures – degree (D), eigenvector (E), closeness (C) and betweenness (B) are summarised providing an overview of (1) how each centrality measure is calculated, and (2) how each defines the prevalence or the most central method of acquiring data in a graph (G).

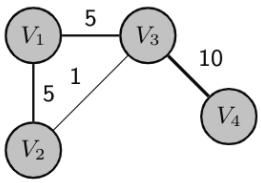
Centrality Measure	Description of Centrality	Implementation
Degree (DC)	Identifies the most central node as the node that has the most direct links to other nodes	$DC_i = \sum_{j=1}^{N} A_{ij\ (i \neq j)}$ (Freeman, 1978)
Eigenvector (EC)	Identifies the most central node as the node that is most linked to other well-linked nodes	$EC_i = \frac{1}{\lambda}\sum_{j=1}^{N} A_{ij}\, v_j$ (Bonacich, 1972)
Closeness (CC)	Identifies the most central node as the node with the smallest sum of the total distances to all other nodes (shortest paths)	$CC_i = \frac{N-1}{\sum_{j=1}^{N} l_{ij}}$ (Sabidussi, 1966)
Betweenness (BC)	Identifies the most central node as the node that exists the most times (acting as a bridge) between a pair of nodes	$BC_i = \sum_{p,q \neq i}^{N} \frac{n_{pq}(i)}{N_{pq}}$ (Freeman, 1978)

Table 1. Definitions for Centrality Measures. A = adjacency matrix; d_i = degree of node i; λ = eigenvalue of A; v = eigenvector associated to λ of A; C_i = sum of distances from node i to all reachable nodes; A_i = number of reachable nodes from node i (not counting i); N = total number of nodes in G; l_{ij} = length of the shortest between nodes i and j; $n_{pq}(i)$ = number of shortest-paths between nodes p and q which pass through i; N_{pq} = total number of shortest paths from p to q.

In each sporting category and year, CMs for each method of acquiring data were assigned a ranking, where the highest CMs were assigned a value of one (most prevalent) and the lowest CMs were assigned a value of 17 (least prevalent). To compare the prevalence of methods of acquiring data between different categories of sport, similarity matrices were created to show differences in the positioning of the methods using the squared Euclidean distance. If a CM did not exist for a node, either because that method was not used that year or had no links to other methods (existed singularly), it had a value of zero. The data contained in these similarity matrices are presented in a selection of heatmaps.

Heatmaps are useful for presenting ordered data, where coloured squares (or pixels) indicate values on a scale from maximal (hot or red colour) to minimal (cold or blue colour). In addition, a large amount of information can be presented without the need to discard potentially useful information which would otherwise happen when using techniques such as principal component analysis (Walker et al., 2012). The volume of information included however, can make a

heatmap appear noisy and arbitrary ordering of the original dataset can prevent patterns and trends in the data. Seriation was therefore used to enable the arrangement of methods of acquiring data that had a high-degree of similarity to be placed closer together on the heatmap and methods of acquiring data that had a low-degree of similarity to be placed further apart (Atkins et al., 1998; Walker et al., 2012).



$$D = \begin{pmatrix} 2&0&0&0 \\ 0&2&0&0 \\ 0&0&3&0 \\ 0&0&0&1 \end{pmatrix} \qquad A = \begin{pmatrix} 0&5&5&0 \\ 5&0&1&0 \\ 5&1&0&10 \\ 0&0&10&0 \end{pmatrix} \qquad L = \begin{pmatrix} 2&-5&-5&0 \\ -5&2&-1&0 \\ -5&-1&3&-10 \\ 0&0&-10&1 \end{pmatrix}$$

(a) Undirected weighted graph (G) (b) Degree matrix (D) (c) Adjacency matrix (A) (d) Laplacian matrix (L)

Figure 2. Example of an undirected, weighted graph (a); its degree matrix (b) and its corresponding square adjacency matrix (c). The number above the link (or line) between two nodes represents the strength of the link between them (link weight). Nodes that are adjacent can be observed in the adjacency matrix, with the value of the entry indicating the link weight. (d) shows the how the un-normalised Laplacian matrix is formed.

The optimal order from seriation was discovered by sorting the second smallest eigenvector of the normalised Laplacian matrix, L (a.k.a the Fiedler vector; equation .1). The Fiedler vector has important applications related to *graph partitioning* and *clustering* (Fiedler, 1973; Slininger, 2013; Von Luxburg, 2007). Therefore, the Fiedler vector was used to re-arrange the similarity matrices prior to constructing the heatmaps for each category of sport to enable methods of acquiring data that had similar CMs to be aligned along the diagonal.

$$L = D^{-1/2}(D-A)D^{-1/2} \qquad (1)$$

A global seriated heatmap of the CMs for each year and each sporting category is also presented. This allows the overall ranking of a method or combination of methods of acquiring data to be identified and provides useful insight into the temporal changes of the prevalence of each method of acquiring data across years. The code generated to complete the analyses above was implemented in MATLAB R2020a, and is available to view at https://www.github.com/petewatson/athletesurveillance

Results

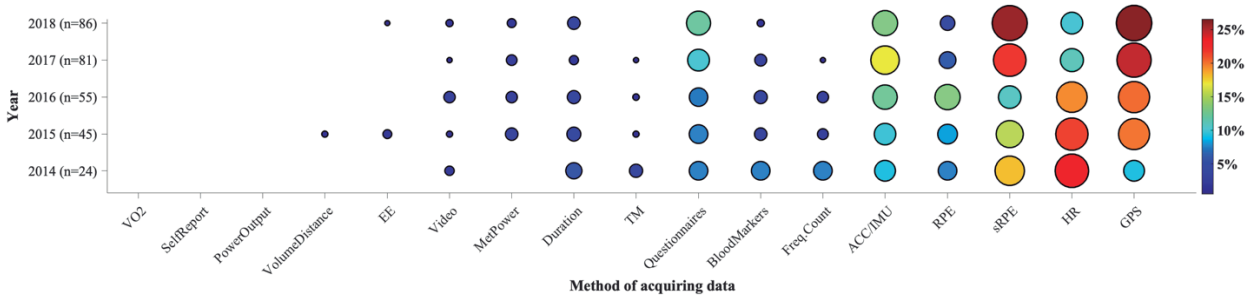
Analysis of the articles included for this review revealed that 303 articles (84.9%) dealt with high-performance/elite/club level athletes and 54 articles (15.1.%) referred to monitoring of recreation/novice/amateur athletes. Due to the small number of articles monitoring lower-level athletes, all articles have been analysed together. Bubble plots for each category of sport are presented in Figure 3. The number of papers in team (n=291) and field-based sports (n=257) are three to four times more than in individual (n=66) and court-based sports (n=67). In team and field-based sports, the larger size and darker coloured bubbles indicate that at some point across the 5-year period, GPS, HR or sRPE have been one of the most frequently used methods of acquiring data. These methods are also positioned to the right-hand side of respective plots to indicate that their relative use across years has been less consistent compared to those methods positioned more centrally on the plots. For example, between 2014 – 2018, the relative use of GPS and sRPE increased and the relative use of HR slightly reduced, while the relative use of

ACC/IMU, although much smaller compared to GPS, HR and sRPE, remained more consistent across years and is positioned further towards to the centre. Compared to other methods of acquiring data, the relative use of questionnaires was also smaller but more consistent across years (central position on the x-axis is the left-hand side (lower band) of methods that are actually used).

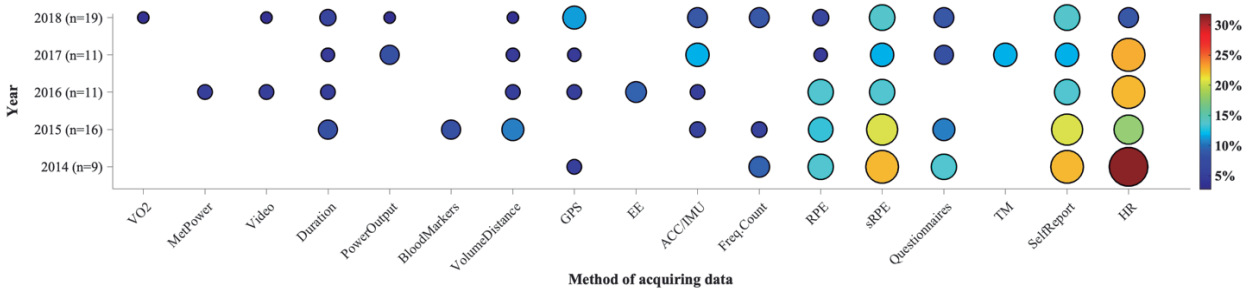
Compared to team and field-based sports, the number of papers available in individual and court-based sports were far fewer. However, the size and colour of the bubbles in individual and court-based sports indicate that the relative use of HR, sRPE and in the case of court-based sports, RPE, have at some point, been the most frequently used methods of acquiring data. The relative use of GPS in these categories of sport however, was far less compared to team and field-based sports. Positioned on the right-hand side of the plots, the relative use of HR across years (from 2015 in court-based sports) had reduced in both individual and court-based sports. In individual sports, the relative use of sRPE and self-report (i.e., training logs), a method whose use is particularly unique to individual sports, have also slightly reduced across the years. In court-based sports, positioned on the right-hand side of the plot, the relative prevalence of RPE and sRPE has varied across years. Questionnaires (performed before or after a training session) were found to be the preferred method over self-report for court-based sports. Demonstrated by an increase in the size of bubble and darkening of the colour, a feature that shows signs of growth across years in all categories of sport, but particularly in court-based sports, is the relative use of ACC/IMU.

Global graphs showing *combinations* of methods of acquiring data for each category of sport summed across all years are presented in Figures 4 and 5. In team and field-based sports, sRPE and GPS are identified as the most prevalent combination of methods of acquiring data due to the strength of the link between them, their close proximity to each other and compared to other methods, their more central position in the network. Strong links also exist between other combinations of internal and external methods of acquiring data such as HR and GPS and HR and ACC/IMU.

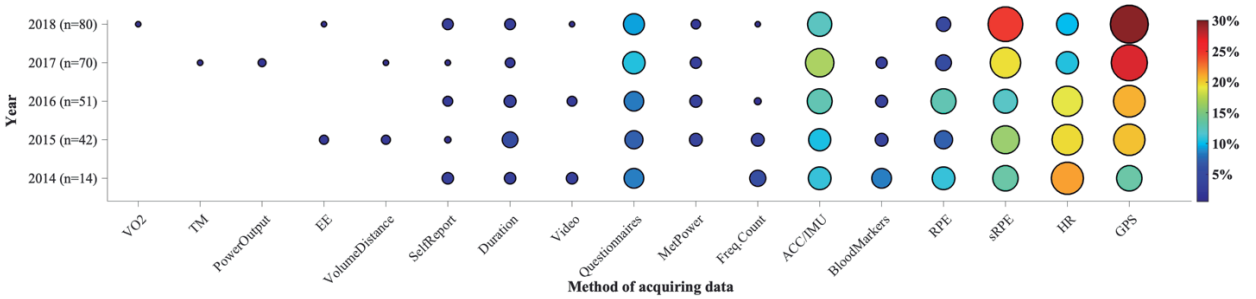
In individual and court-based sports, HR and sRPE, which are both internal methods of acquiring data are identified as the most prevalent combination of methods. In individual sports, internal methods of acquiring data are clustered in the centre and external methods are pushed to the outer layer of the network. Where combinations of internal and external methods of acquiring data do exist, the external method is most commonly ACC/IMU. In court-based sports, internal methods of acquiring data are most often combined, but when links do occur between internal and external methods, they are strongest between HR and ACC/IMU.



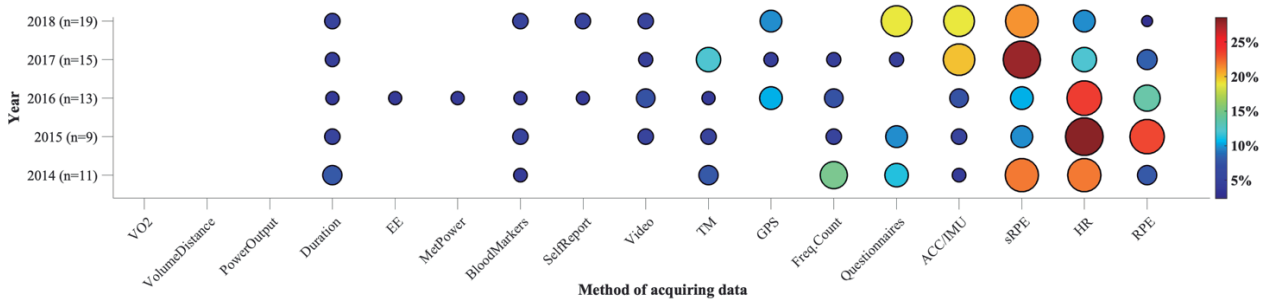
(a) Team



(b) Individual

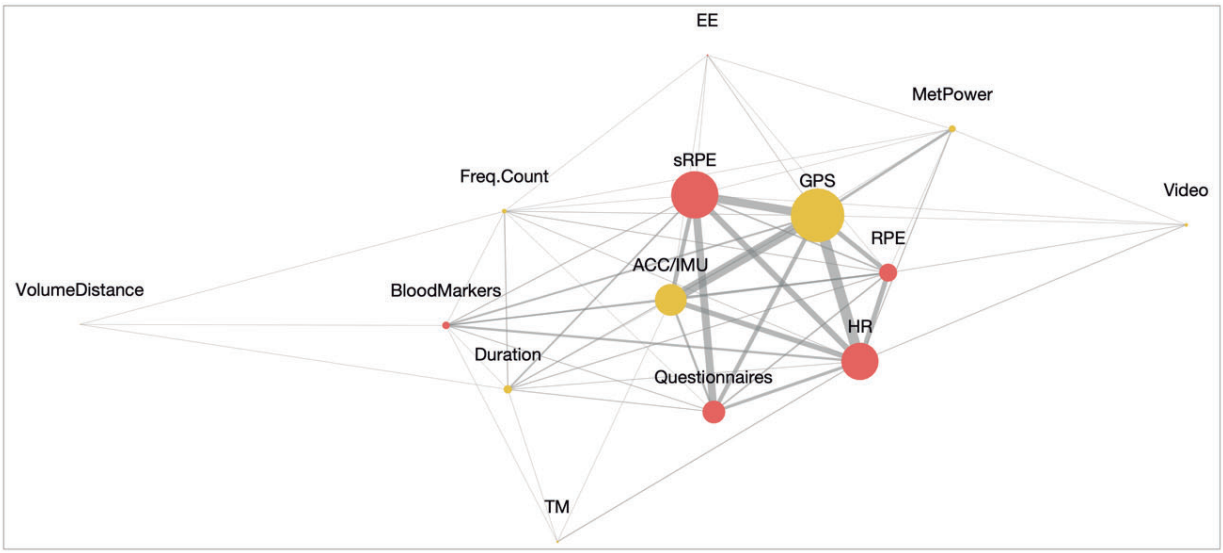


(c) Field-based



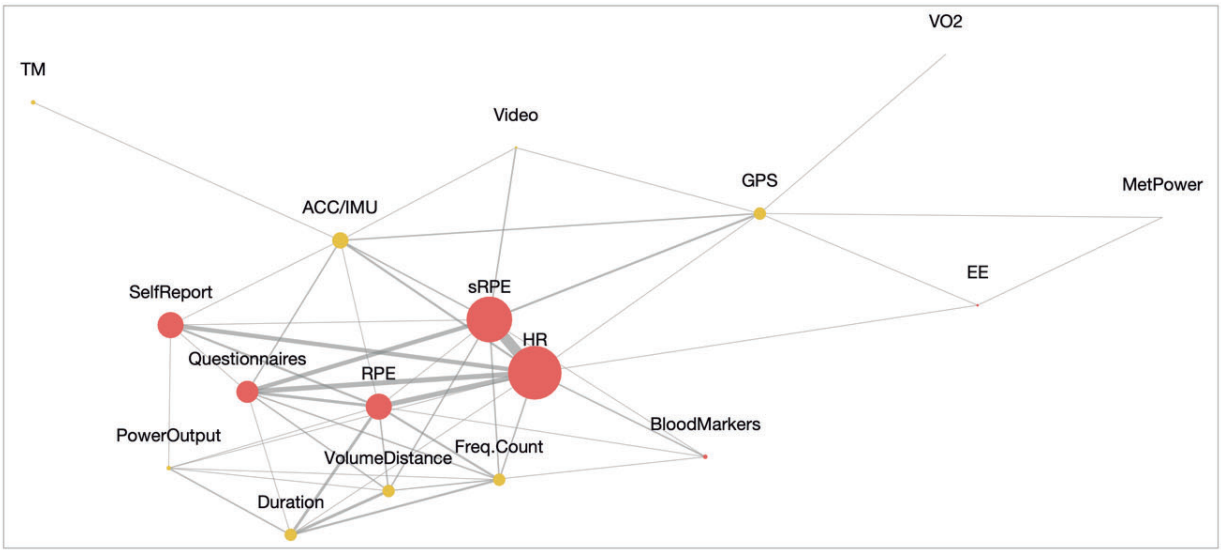
(d) Court-based

Figure 3. Bubble plots for (a) Team (b) Individual (c) Field-based and (d) Court-based sports show the proportion of each method of acquiring data by each year (2014-2018). The size and colour of the bubble is proportional to the number of methods used in a particular year. The order of the methods on the x-axis from left (relative use of method is most consistent across years) to right (relative use of methods is least consistent across years) are determined by the standard deviation of the proportion of each method used across years to indicate how consistently a method was acquired. The most consistent methods that are actually used, are positioned more centrally on the plot.



*Density scores – 2014: 0.2794; 2015: 0.4412; 2016: 0.3236; 2017: 0.3309; 2018: 0.3015
** The following methods of acquiring data are not present: VO_2, SelfReport, PowerOutput

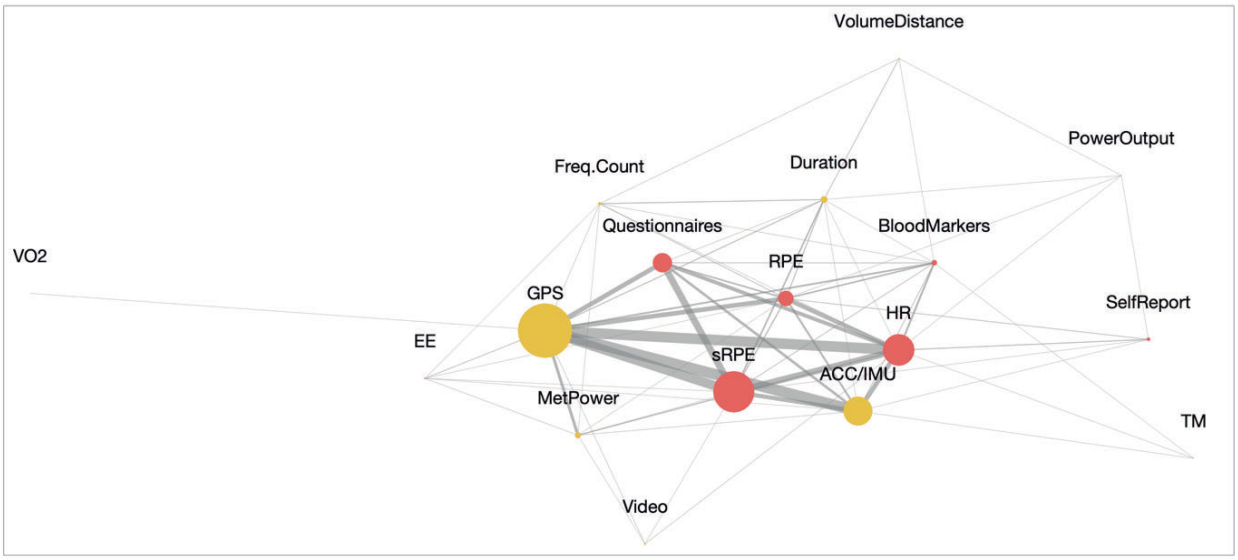
(a) Team sports



*Density scores – 2014: 0.1176; 2015: 0.2353; 2016: 0.1691; 2017: 0.2132; 2018: 0.2574

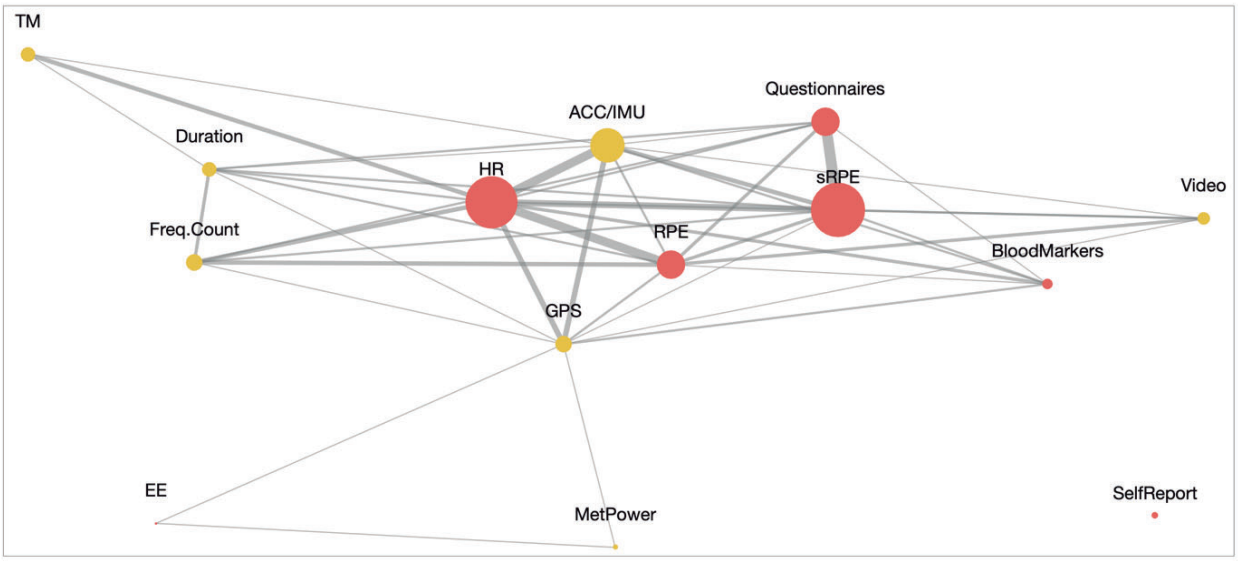
(b) Individual sports

Figure 4. Graphs for (a) Team and (b) Individual sports (summed over 2014-2018). The strength of the link between two methods of acquiring data is represented by the thickness of the edge that joins the two corresponding nodes together. Methods with the strongest links are positioned towards the centre of the network. Nodes representing internal methods of acquiring data are coloured red and nodes representing external methods of acquiring data are coloured yellow.



*Density scores – 2014: 0.2647; 2015: 0.4191; 2016: 0.2941; 2017: 0.3676; 2018: 0.2941

(a) Field-based sports

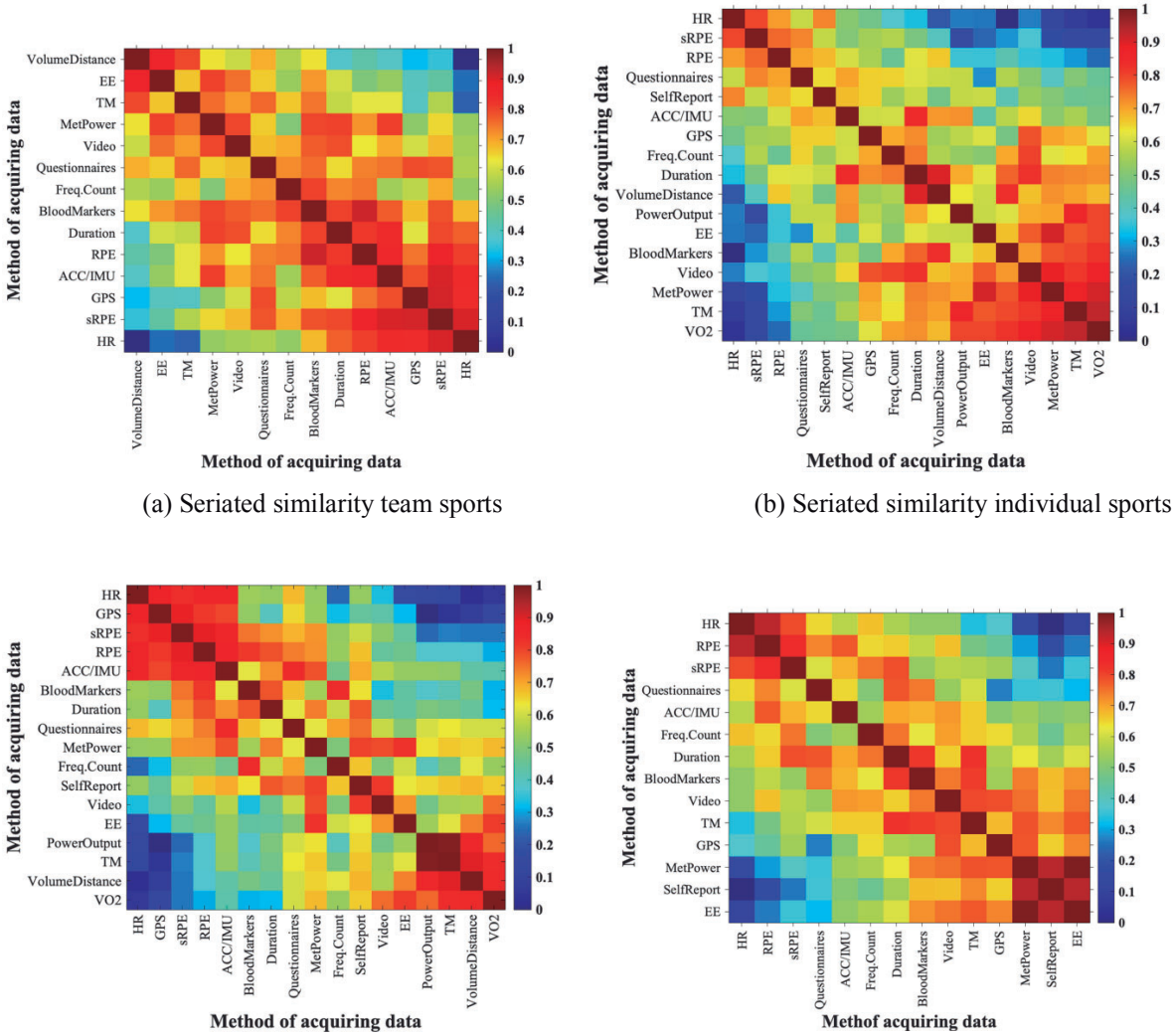


*Density scores – 2014: 0.1912; 2015: 0.1912; 2016: 0.2206; 2017: 0.1618; 2018: 0.2132

** The following methods of acquiring data are not present: VO_2, VolumeDistance, PowerOutput

(b) Court-based sports

Figure 5. Graphs for (a) Field-based and (b) Court-based sports (summed over 2014-2018). The strength of the link between two methods of acquiring data is represented by the thickness of the edge that joins the two corresponding nodes together. Methods with the strongest links are positioned towards the centre of the network. Nodes representing internal methods of acquiring data are coloured red and nodes representing external methods of acquiring data are coloured yellow.



(a) Seriated similarity team sports

(b) Seriated similarity individual sports

(c) Seriated similarity field-based sports

(d) Seriated similarity court-based sports

Figure 6. Similarity matrices of methods of acquiring data for each category of sport (a) Team; (b) Individual; (c) Field-based and (d) Court-based after seriation with rows and columns permuted w.r.t their corresponding Fiedler vectors. Seriation places similar elements (dark red) so they lie closer to the diagonal and pushes dissimilar elements (cooler colours) to the edge.

In contrast to GPS being the most prevalent external method in team and field-based sports, in individual and court-based sports, ACC/IMU is well connected to a range of internal methods and therefore appears to be the most prevalent external method of acquiring data.

Graph density scores for each category of sport across 2014 – 2018 also help to quantify the layout of each graph. In comparison to individual (0.12 – 0.26) and court-based sports (0.16 – 0.22), team (0.28 – 0.44) and field-based sports (0.26 – 0.42) have higher density scores across the years. In team and field-based sports, these support a more obvious clustering of methods, aesthetically forming outer and inner layers that contain more frequently used methods (based on node size) and commonly used combinations of methods (based on link strength).

Similarity matrices derived from ranking CMs for each method of acquiring data for team, individual, field- and court-based sports, are presented as heatmaps in Figures 6(a),(b),(c) and (d) respectively. In team sports, the dark coloured pixel representing sRPE (internal method) and GPS (external method) on the heatmap indicates that the CMs for both these methods are

highly similar. In addition to visually interpreting networks and the strength of a connection between these methods (Figure 6(a)), this information confirms that the position and therefore the position of sRPE and GPS within the network are highly similar.

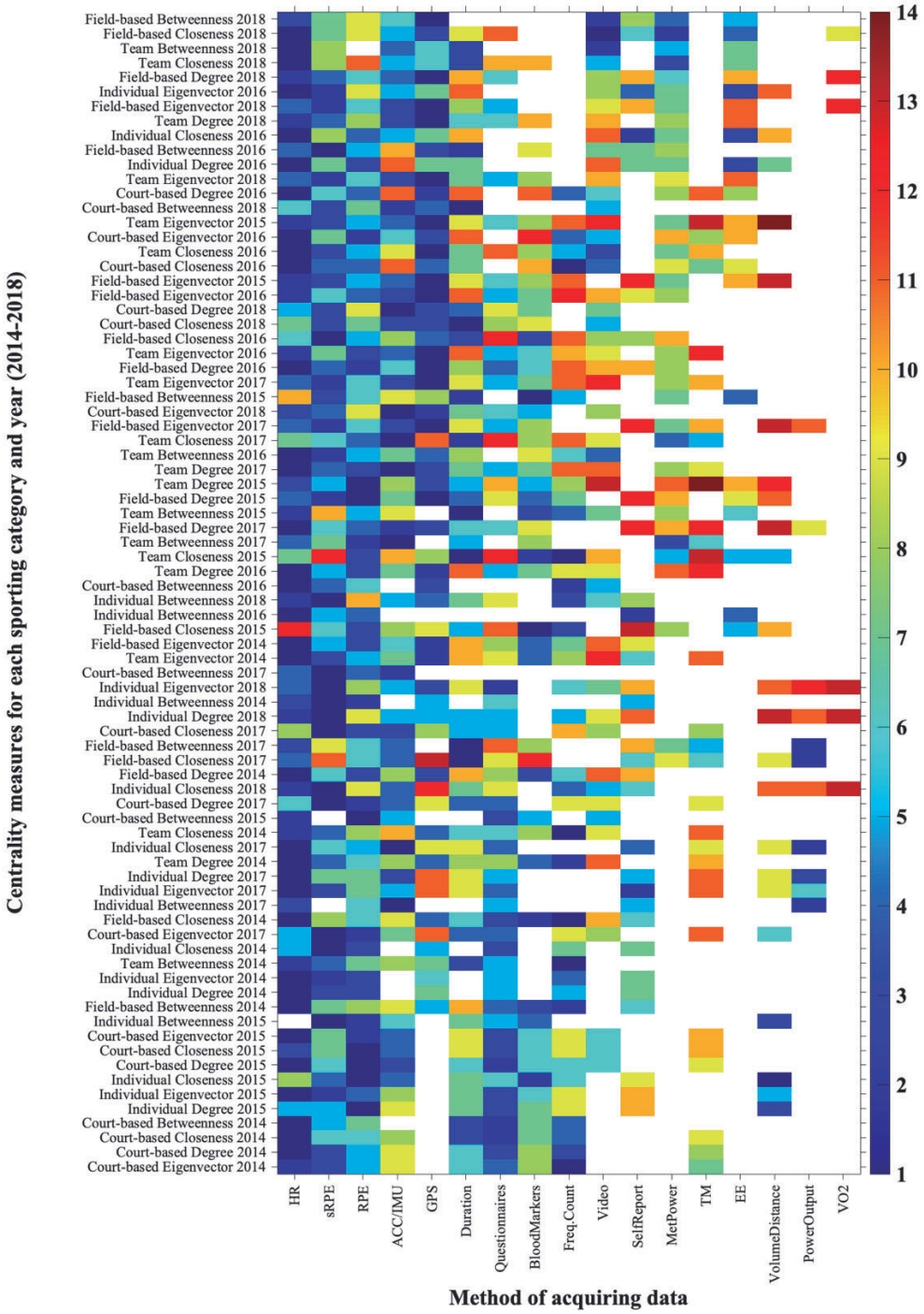


Figure 7. Global seriated heatmap showing each method of acquiring data ranked by prevalence based on their corresponding centrality measures for each category of sport and by year (2014 -2018). Methods of acquiring data with high prevalence (low numbers refer to a higher ranking/cooler colour) and low prevalence (high numbers refer to low ranking/hotter colour) are placed closer together. Applying Seriation to the ordering of methods along the x-axis results in HR being positioned on the left-hand side and helps identify it as the most prevalent method of acquiring data. White spaces indicate that no CM was present for that method.

Similarity scores could be interpreted by themselves in order to compare the relative position of methods, independent of any connections between methods of acquiring data within the

network. For example, in individual sports (Figure 6(b)), HR and self-report have highly similar CMs and therefore similar levels of use in relation to other methods in the network. However, their different physical positions in the network and the lack of any connection between these methods highlights that the lone interpretation of similarity scores (without insight from the network) to infer the prevalence of a combined collection of each pair of methods, should be cautioned against.

Methods of acquiring data ranked by CM values within each sporting category and across all years are presented in a global seriated heatmap in Figure 7. Using CMs to quantify prevalence revealed that HR, RPE and sRPE (in order), which are all internal methods, were the top three most prevalent methods of acquiring data across team, individual, field- and court-based sports between 2014-2018. ACC/IMU and GPS, which are external methods of acquiring data, were identified respectively as the fourth and fifth most prevalent methods of acquiring data across team, individual, field- and court-based sports between 2014-2018. Although a larger size of node in bubble plots and graphs indicate that GPS was used more often than ACC/IMU, a higher number of links between ACC/IMU and other methods of acquiring data within the network means that CMs ranked the prevalence of ACC/IMU higher than GPS.

Discussion

To our knowledge, this is the first scoping review of this scale (357 articles) to summarise the prevalence of methods used in research to acquire data from athletes across four sporting categories: team, individual, field-based and court-based sports. To achieve this, SNAM-based techniques were employed and included the creation of informative network visualisations (graphs) which provided insight on the prevalence of methods used to acquire data based on the size and location of nodes relative to each other, the number and strength of the links between nodes of the same type and of different types (internal/external methods) and a measure of network density (number of links relative to potential number of links possible). As a visual summary, networks for each category of sport can be used independently of any other analysis within this review to identify how often particular combinations of methods used to acquire data from athletes have been used in research. This summary can be used to provide reassurance for a choice of method or combination of methods as well as alternatives to enable those responsible for implementing surveillance systems in practice decide which methods to employ relative to their logistical circumstances (Bourdon et al., 2017; Campbell et al., 2017), whilst also satisfying recommendations for using multiple methods and preferably internal and external methods to track athlete progression (Soligard et al., 2016; Bourdon et al., 2017; Impellizzeri et al., 2019). Four common CMs (degree, eigenvector, closeness, betweenness) that reflected how many times each method (node) was used, how well connected it was to other methods (nodes) and the proximity of its location to other methods in the network, were also calculated. These provided quantitative values that helped to highlight and describe unseen inner workings of the networks. The visual presentation of CMs in heatmaps, ordered based on Fiedler vector seriation, further enabled the most prevalent methods that were collected *in combination* with other methods, to be *seen* and identified in each category of sport.

Prevalent combinations of methods used to acquire data in practice

With reference to aim 1, a summary of CMs from all four sporting categories (Figure 7) reveals that the most prevalent internal methods collected in combination with other methods in the same paper were (in order) HR, sRPE and RPE. The most prevalent external methods collected in combination with other methods were (in order) ACC/IMU and GPS. The prevalence of

ACC/IMU over GPS may seem surprising given that the size of node in bubble plots and graphs was typically largest for GPS compared to ACC/IMU, especially in team and field-based sports. However, the relative absence of GPS in individual and court-based sports, coupled with the relatively prevalent and consistent use of ACC/IMU, plus its use in combination with a range of other methods, helps ACC/IMU to maintain a relatively central position in team, field-based and court-based networks. Based on CMs that are informed by the positioning and connectivity of nodes with one another and as depicted in networks, the relative use of ACC/IMU in combination with other methods is concluded as being more prevalent compared to GPS. If only vote-counts (bubble plots) were employed to sum the number of times each method of acquiring data was used, the potential to have identified the emergence and prevalence of ACC/IMU in combination with HR or sRPE, would have been hidden.

With reference to aim 2, to help identify gaps in the literature, simple comparisons of global network plots firstly reveal that in comparison to team and field-based sports, less research is undertaken in individual and court-based sports (limited number of papers included within this review these area). With reference to aim 3, differences in the structure of networks between sports can also be seen. For instance, the graphs for team and field-based sports (which are very similar due to a high number of articles analysing football and rugby, both of which are classified as team and field-based sports) demonstrate a well-defined inner core and outer layer of nodes. The inner core in field and team-based sports are made up of a mixture of strongly linked internal (e.g., HR, sRPE) and external (e.g., GPS, ACC/IMU) methods of acquiring data. This demonstrates that research detailing athlete monitoring and surveillance in these types of sport tend to comply with recommendations to use multiple methods of monitoring (Soligard et al., 2016; Bourdon et al., 2017; Impellizzeri et al., 2019). These well-defined layers also indicate that if researchers are to experiment with other methods of acquiring data, they mostly do so either as a supplement to the more common (core) methods of acquiring data or in rarer cases, collect data using a single less frequently used method.

The existence, if any, of an inner and outer layer of nodes in the global network plots for individual and court-based sports is less well defined and indicates that these types of sports comply less with recommendations to use internal and external methods of acquiring data when monitoring athletes. For individual sports, the inner layer consists of mainly internal methods of acquiring data (e.g., HR, sRPE and Questionnaires) and external methods are pushed to the outer layer. While internal and external methods of acquiring data have still been collected in combination in some research, for the majority of articles in individual sports, internal methods take prevalence over external. In court-based sports, the inner layer also consists mainly of internal methods (similar to individual sports), with the introduction of a few external methods. Whilst court-based sports are less researched compared to team and field-based sports, there is some evidence that internal and external methods of acquiring data are used in combination by a relatively small sample of articles. This may be an indication that more research in sports within this category in the future may combine internal and external methods of acquiring data and that with a greater number of articles, the structure of this network may appear more similar to the structure shown in team and field-based sports.

In team and field-based sports, HR (internal) and GPS (external) are strongly linked whereas in individual and especially court-based sports, any evidence for the joint collection of internal and external measures of load arises from the collection of HR and ACC/IMU. The prevalence of these particular internal and external methods is likely a function of companies introducing wearable devices that contain both an ACC/IMU, GPS and HR capability (via HR strap or optical sensor). In team and field-sports however, ACC/IMU is reported in the literature far less than GPS, despite devices being capable of recording and providing acceleration data. The emergence of ACC/IMU as a highly prevalent method of acquiring data in court-based sports,

is most likely due to the limitation of using of GPS devices within indoor environments or smaller areas, which are typically associated with court-based sports. Although Local Positioning Systems (LPS) are available for small stadiums and indoor use (where satellite coverage is deficient), at present the expense of installation and calibration has limited their use (Theodoropoulos et al., 2020). Therefore, to replace GPS, the majority of court-based sports have looked to advances in the creation and interpretation of accelerometer-derived metrics of training load (Young et al., 2016; Staunton et al., 2017; Bailey et al., 2017). Out of necessity, court-based sports may drive future research in this area and encourage this method of acquiring data to also be used more in team and field-based sports.

Continuing to reflect on Aim 3, similarities between different types of sport are also apparent. Although not the most prevalent methods of acquiring data, the analysis of articles in this review indicates that Questionnaires and Self-Reporting methods are well used across all categories of sport. Questionnaires in particular appear, to be collected more in isolation rather than in combination with other methods. This could be a reflection of some surveillance systems being implemented in circumstances where there are limited resources to support additional methods of monitoring. If this is the case, Saw (2016) suggests that Questionnaires can be used as a lone method of monitoring. Questionnaires and Self Reporting methods of acquiring data may be particularly important to help monitor aspects of recovery and rest between training bouts (Coyne et al. et al., 2018). However, the central position of Questionnaires in networks also makes them well placed to be used in combination with other methods of acquiring data. As we move into an era where monitoring athletes 24/7 may provide further insights into programming including a greater emphasis on rest and recovery (e.g., the acquisition of sleep data, physical activity and sedentary behaviour combined with Ecological Momentary Assessment), the use of wellness scores and activity logs via Questionnaires and/or Self-Report in athlete surveillance programmes alongside other methods such as accelerometry, will likely increase.

Practical implications of this review

When implementing an athlete surveillance system, it is recommended that multiple methods and preferably internal and external methods of acquiring data are used to track athlete progression (Soligard et al., 2016; Bourdon et al., 2017; Impellizzeri et al., 2019). Consulting a list of the strengths and limitations of methods of acquiring data is also recommended (Bourdon et al., 2017). Until now however, there has been no further information available to provide an indication of how methods may be used in combination with each other, which could help support method selected. Therefore, with a focus on supporting the selection of both internal and external methods of acquiring data in practice based on logistical circumstances, visual information summarising the prevalence of different combinations of methods used in research, may be used as follows:

1) Review a detailed and up to date list of the strengths and limitations for a range of external and internal methods of acquiring data (e.g., Bourdon et al., 2017) and consider these throughout the next steps.
2) Review the range of network plots and rank-ordered heatmaps presented in this review which detail the prevalence of different combinations of methods used to acquire data from athletes. A summary guide with examples to help interpret these figures and choose suitable combinations of methods that meet logistical circumstances is as follows:
    i) Study the networks for each type of sport to see which methods are most prevalent (look for the largest sized nodes positioned most centrally – e.g., in individual sports

the largest most centrally positioned nodes are HR and sRPE). Studying all networks helps you to appreciate the range and prevalence of methods used in each category of sport.

ii) If you are interested in one category of sport then select that category and study the thickness of the lines between internal and external methods. The thickest and shortest lines between two methods indicates that these two methods are most frequently used together in research, to monitor athletes in this category of sport.

iii) Based on the strengths and limitations of practically incorporating the most prevalent combination of methods in practice to consistently monitor athletes, decide whether there is sufficient financial support for equipment and staff costs, staff time, database size and database security for collecting, inputting and managing the acquired data.

iv) If based on logistical circumstance, it is better not to use the most prevalent methods presented but instead seek alternative methods with less logistical burden, use the network to identify alternative combinations of methods of acquiring data. Alternative methods are indicated in the networks by slightly smaller node sizes, slightly thinner lines and slightly longer lines connecting a pair or more methods. It would be advantageous if these methods were still positioned relatively centrally within the network although at present, for categories of sport that are less researched (e.g., individual and court-based sports), the size of the inner core layer is relatively small and therefore alternative methods may be positioned closer towards the edges of these networks. If differences in position or strength of connection between methods presented in networks are difficult to read at this point, then consider studying the global heatmap for respective categories of sport (Figure. 7).

v) Alternative methods for acquiring data can also be identified in respective heatmaps. Methods are ordered along the axes of each heatmap based on a measure of how similar (or dissimilar) their central position is in the network and how connected they are to other methods (identified by their CMs). HR for instance is the top-ranked method of acquiring data in individual sports and is deep red in colour. The second most central/prevalent method is sRPE and lighter-red in colour. The prevalence of these methods is fairly obvious to see in the network, but the prevalence of methods positioned after these top two are more difficult to see in the network. Whilst the colours are lighter for each method further down the order/axis, methods coloured orange/yellow are still used relatively often. These methods are therefore alternatives that may be easier to incorporate relative to logistical circumstances.

To understand which measures of training load (derived from methods) might be most relevant to monitoring training progression in a particular sport, readers are advised to appraise the evidence first-hand (Impellizzeri et al., 2020b; 2020b). With this recommendation in mind, integrated devices permitting multiple methods of acquiring data (e.g., GPS, ACC/IMU and HR) to be incorporated in a single device, may present an interesting option to facilitate the capture of multiple types of data from athletes in an efficient manner. In this instance, an integrated device could be seen as 'good value for money' relative to the capacity to collect a lot of information from athletes. However, the collection of multiple types of data and high volumes of data may also present a potential dilemma to surveillance system personnel and coaching staff. To enable data to provide valuable feedback on athlete development and avoid it being wasted, it needs to be analysed, presented and interpreted in an applied setting. Whilst an integrated device may appear to be a cost-effective investment, the methods incorporated and the validity of the measures of training load derived, should still be evaluated in accordance with published research (Impellizzeri et al., 2020b; 2020b).

Limitations

Article selection and application

A key strength of this scoping review is its ability to summarise and map information from a large number of articles (n=357). To achieve this, an iterative process based on a review of 34 articles (2014) was carried out to further clarify the inclusion/exclusion criteria for the initial article selection. Following this however, only one author reviewed and extracted data for all remaining articles. The articles selected by another research team, may be different to the ones included here. A number of additional steps not considered in this review, but which could influence the amount of data reviewed, is the inclusion of grey literature and a further step outlined by Arksey and O'Malley (2015). This includes a consultation exercise with personnel outside of the review team (i.e., coaches and sport scientists) to ratify article inclusion/exclusion criteria towards methods used to acquire monitoring data outside of the published literature.

Rather than obtaining information on methods used in practice from those responsible for implementing surveillance systems, this review has summarised methods used to monitor athletes in published research. There may therefore be a difference between methods used in research and methods used in practice which could limit how transferable this information is to an applied setting. Competition level may also influence the choice of methods used to monitor athletes. The research included in this review is heavily weighted towards team and field-based sports and within these categories, the monitoring of professional and/or elite level athletes. The methods presented in these categories of sport may therefore not reflect methods available or chosen to monitor athletes at a lower competition level. Based on a review of literature, it's also important to acknowledge contributing factors such as study replication, which may influence what other research also does rather than independently choosing and justifying each choice of method.

The use of centrality measures

It is important to note some limitations in the CMs selected to identify the most important methods (nodes) and combinations of methods of acquiring data. Firstly, whilst certain CMs may be optimal for certain network applications, selection should be made on a case-by-case basis as their application is context specific. With no prior knowledge as to which CMs were best for identifying the most prevalent methods of acquiring data, four basic CMs (Degree, Eigenvector, Closeness and Betweenness) were chosen. There are however many other CMs available.

Secondly, the CMs chosen may not be appropriate for all nodes in a network. CMs that were optimal for identifying well linked methods (i.e., HR, GPS, sRPE etc.) may not be optimal for the remaining nodes in the network that had weak links or no links. This is evident for Self-Report (Figure 4b), which was identified as being one of the most prevalent methods of acquiring data, but this was not registered by CMs as it was collected as a singular method with no links to other nodes. The application of CMs therefore has its challenges in depicting how often methods with zero or very few links are used. Because of this, the order of methods at the bottom of the list is not definitive.

Thirdly, the most prevalent methods of acquiring data overall, were presented through the seriated ranking of methods and by comparing the differences between the ranking location (as seen in Figure 7). However, this method does not take into account the magnitude of the difference in prevalence between each rank.

While it is important to acknowledge the limitations of CMs, they were applied in addition to the analysis of bubble plots detailing methods of acquisition across years and visual interpretation of global network plots (average of 5-years). Therefore, based on the underlying

data and structure of the network plots, analysis of any additional CMs (other than the four used in this review) would not be expected to significantly influence the overall findings from this review.

Conclusion

The application of SNAM-based techniques summarising combined methods of acquiring data in research over a 5-year period, have confirmed that team and field-based sports adhere strongly to recommendations for capturing internal and external data in athlete surveillance programmes. The range of different combinations of methods used to achieve this provide a useful point of reference to enable those responsible for implementing surveillance systems in these types of sports a number of options for achieving this recommendation whilst also meeting a recommendation to consider their logistical circumstances. In team and field-based sports, the collection of HR and/or sRPE (internal) with GPS and/or ACC/IMU (external) were the most prevalent combinations, but respective alternatives also included Questionnaires (internal) with GPS and/or ACC/IMU (both external). In contrast, individual and court-based sports, which are less richly researched, have tended to rely on the sole collection of internal methods of acquiring data, most commonly HR and sRPE. There was some evidence for the combined collection of internal and external methods of acquiring data in court-based sports with HR and/or sRPE sometimes being collected in combination with ACC/IMU. Despite recommendations for using internal and external methods of acquiring data in athlete surveillance, there appears to be a considerable gap in the surveillance of athletes in individual and court-based sports that would benefit from some targeted research. The application of SNAM-based techniques for summarising methods used in research has revealed an opportunity for court-based sports in particular, to lead the way in the use of ACC/IMU to monitor athletes. The SNAM-based techniques presented in this scoping review provide coaches, sport-scientists and researchers with a valuable and unique resource that summarises the prevalence of different combinations of methods used to acquire data from athletes in research. Based on this review, guidance is provided to help those responsible for establishing and managing athlete surveillance systems to select prevalent combinations of internal and external methods of acquiring data from athletes, relative to logistical circumstances.

References

Arksey, H., & O'Malley, L. (2005). Scoping studies: Towards a methodological framework. *Int J Soc Res Meth*, 8(1), 19-32. doi: 10.1080/1364557032000119616

Atkins, J., & Boman, E.(1998). A spectral algorithm for seriation and the consecutive ones problem, *SIAM J Comput*. 28(1), 297–310. doi: 10.1137/S0097539795285771

Bailey, J.A., Gastin, P.B., Mackey, L., Dwyer, D.B. (2017). The Player Load Associated With Typical Activities in Elite Netball. *Int J Sports Physiol Perform*. 12(9), 1218-1223. doi: 10.1123/ijspp.2016-0378

Bonacich, P. (1972). Factoring and weighting approaches to status scores and clique Identification. *J Math Social*. 2(1), 113–120. doi: 10.1080/0022250X.1972.9989806

dos Santos, R.P., & Lopes, G.R. (2019). Thematic series on Social Network Analysis and Mining. J Internet Serv Appl 10, 14. doi: 10.1186/s13174-019-0113-z

Bourdon, P., Cardinale, M., Murray, A., Gastin, P., Kellmann, M., Varley, M., Gabbett, T., Coutts, A., Burgess, D., Gregson, W., & Cable, T. (2017). Monitoring Athlete Training Loads: Consensus Statement. *Int J Sports Physiol Perform*, 12(S12), S2161-S2170. doi: 10.1123/IJSPP.2017-0208

Buchheit, M., Simpson, M., Al Haddad, H., Bourdon, P., & Mendez-Villanueva, A. (2012). Monitoring changes in physical performance with heart rate measures in young soccer players. *Eur J Appl Physiol*, 112(2), 711-23. doi: 10.1007/s00421-011-2014-0

Campbell, B., Bove, D., Ward, P., Vargas, A., & Dolan, J. (2017). Quantification of Training Load and Training Response for Improving Athletic Performance. *Str Cond J*, 39(5), 3-13. Doi: 10.1519/SSC.0000000000000334

Coyne, J.O., Haff, G.G, Coutts, A,J., Newton, R.U., & Nimphius, S. (2018). The current state of subjective training load monitoring – A practical perspective and call to action. Sports medicine-open. 4(1), 58. doi: 10.1186/s40798-018-0172-x

Drew, M., & Finch, C. (2016). The Relationship Between Training Load and Injury, Illness and Soreness: A Systematic and Literature Review. *J Sports Med*. 46, 861-83. doi: 10.1007/s40279-015-0459-8

Freeman, L. (1977). A set of measures of centrality based on betweenness. *Sociometry*, 40(1), 35–41. doi: 10.2307/3033543

Fiedler, M. (1973). Algebraic connectivity of graphs. *Czech Math J*, 23, 298–305. doi: 10.21136/CMJ.1973.101168

Fruchterman, T. & Reingold, E. (1991), Graph drawing by force-directed placement. *Softw: Pract. Exper*. 21, 1129-1164. doi:10.1002/spe.4380211102

Haddad, M., Stylianides, G., Djaoui, L., Dellal, A., & Chamari, K. (2017). Session-RPE Method for Training Load Monitoring: Validity, Ecological Usefulness, and Influencing Factors. *Frontiers in Neuroscience*. 11, 612. doi: 10.3389/fnins.2017.00612

Halson, S. (2014). Monitoring Training Load to Understand Fatigue in Athletes. *Sports Med*. 44(S2), 139-147. doi: 10.1007/s40279-014-0253-z

Himelboim, I. (2017). Social Network Analysis (Social Media). In *The International Encyclopedia of Communication Research Methods* (eds J. Matthes, C.S. Davis and R.F. Potter). doi: 10.1002/9781118901731.iecrm0236

Impellizzeri, F.M., Marcora, S.M., Coutts, A.J. (2019). Internal and External Training Load: 15 Years On. *Int J Sports Physiol Perform*. 14(2), 270-273. doi: 10.1123/ijspp.2018-0935

Impellizzeri, F.M., Menaspà, P., Coutts, A.J., Kalkhoven, J., Menaspà, M.J. (2020). Training Load and Its Role in Injury Prevention, Part I: Back to the Future. *J Athl Train*. 55(9), 885-892. doi: 10.4085/1062-6050-500-19

Impellizzeri, F.M., McCall, A., Ward, P., Bornn, L., & Coutts, A.J. (2020). Training Load and Its Role in Injury Prevention, Part 2: Conceptual and Methodologic Pitfalls. *J Athl Train*. 55(9), 893-901. doi: 10.4085/1062-6050-501-19

Leppink, J., & Pérez-Fuster, P. (2019). Social Networks as an Approach to Systematic review. *Health professions Education*. 5(3), 218-224. doi: 10.1016/j.hpe.2018.09.002.

Newton, M., Owen, A., & Baker, J. (2019). Monitoring External and Internal Training Loads: Relationships with Injury Risk in Professional Soccer: A Review. *EC Orthopaedics*, 10(9), 686-697. Retrieved from https://www.ecronicon.com/ecor/pdf/ECOR-10-00478.pdf

Sabidussi, G. (1966). The centrality index of a graph. *Psychometrika*, 31, 581–603. doi: 10.1007/BF02289527

Sands, W. Kavanaugh, A. Murray, S. McNeal, J. & Jemni, M. (2017). Modern Techniques and Technologies Applied to Training and Performance Monitoring. *Int J Sports Physiol Perform*, 12(S2), S2-63-S2-72. doi: 10.1123/ijspp.2016-0405

Staunton, C., Wundersitz, D., Gordon, B., Kingsley, M. (2017). Construct Validity of Accelerometry-Derived Force to Quantify Basketball Movement Patterns. *Int J Sports Med*. 38(14),1090-1096. doi: 10.1055/s-0043-119224

Saw, A., Luana, C., & Gastin, P. (2016). Monitoring the athlete training response: subjective self-reported measures trump commonly used objective measures: a systematic review. *Brit J Sports Med*, 50, 281-291. doi: 10.1136/bjsports-2015-094758

Soligard, T., Schwellnus, M., T., Alonso, J., Bahr, R., Clarsen, B., Dijkstra, P., Gabbett, T., Glesson, M., Hägglund, M., Hutchinson, M., Van Rensburg, C., Khan, K., Meeusen, R., Orchard, J., Pluim, B., Raftery, M., Budgett, R., Engebretsen, L. (2016). How much is too much? (Part 1) International Olympic Committee consensus statement on load in sport and risk of injury. *Brit J Sports Med*, 50, 1030-1041. doi: 10.1136/bjsports-2016-096581

Schwellnus, M., Soligard, T., Alonso, J., Bahr, R., Clarsen, B., Dijkstra, P., Gabbett, T., Glesson, M., Hägglund, M., Hutchinson, M., Van Rensburg, C., Meeusen, R., Orchard, J., Pluim, B., Raftery, M., Budgett, R., Engebretsen, L. (2016). How much is too much? (Part 2) International Olympic Committee consensus statement on load in sport and risk of illness. *Brit J Sports Med*, 50, 1043-1052. doi: 10.1136/bjsports-2016-096572

Slininger, B. (2013): Fiedler's Theory of Spectral Graph Partitioning. *University of California*. Retrieved from http://www.cs.ucdavis.edu/~bai/ECS231/returnsfinal/Slininger.pdf

Theodoropoulos, J.S., Bettle, J., & Kosy, J.D. (2020). The use of GPS and inertial devices for player monitoring in team sports: A review of current and future applications. *Orthopedic reviews*. 12(1). 7863. https://doi.org/10.4081/or.2020.7863

Tricco, A., Lillie, E., Zarin, W., O'Brien, K., Colquhoun, H., Levac, D., & et al. (2018). PRISMA Extension for Scoping Reviews (PRISMA-ScR): Checklist and Explanation. *Ann Intern Med*, 169(7), 467–473. doi: 10.7326/M18-0850

Walker, D., Everson, R., & Fieldsend, J. (2013). Visualizing Mutually Nondominating Solution Sets in Many-Objective Optimization. IEEE Transactions on Evolutionary Computation, 17(2), 165-184. doi: 10.1109/TEVC.2012.2225064

Williams, S., Trewartha, G., Cross, M., Kemp, S., & Stokes, K. (2016). Monitoring What Matters: A Systematic Process for Selecting Training-Load Measures. *Int J Sports Physiol Perform*, 12(S2), S2-101-S2-106. doi: 10.1123/ijspp.2016-0337

von Luxburg, U. (2007). A Tutorial on Spectral Clustering. *Stat Comput*, 17(4), 395–416. doi: 10.1007/s11222-00

Young, C.M., Gastin, P.B., Sanders, N., Mackey, L., Dwyer, D.B. (2016). Player Load in Elite Netball: Match, Training, and Positional Comparisons. *Int J Sports Physiol Perform*. 11(8), 1074-1079. doi: 10.1123/ijspp.2015-0156