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SPORTS PERFORMANCE

Time to embrace the complexity when analysing GPS data? A systematic review of contextual factors on match running in rugby league

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ABSTRACT

This systematic review aimed to identify and summarise associations between currently identified contextual factors and match running in senior male professional rugby league. Eligible articles included at least one contextual factor and used GPS to measure at least one displacement variable within competitive senior, male, professional rugby league matches. Of the 15 included studies, the identified contextual factors were grouped into factors related to individual characteristics (n = 3), match result (n = 4), team strength (n = 2), opposition strength (n = 3), match conditions (n = 6), technical and tactical demands (n = 6), spatial and temporal characteristics (n = 7), and nutrition (n = 1). Speed was the most commonly reported measure of match running (100%), followed by distance (47%), and acceleration (20%). Inconsistencies were found between studies for most contextual factors on match running. Higher speeds were generally associated with higher fitness, encountered earlier in the match and whilst defending. All 15 studies utilised a univariate approach to quantify associations of a contextual factor. The inconsistencies found in the associations of given contextual factors highlight the complex and multi-faceted nature of match running. Therefore, practitioners should consider contextual factors when analysing and interpreting GPS data.

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KEYWORDS
Contextual influence; match demands; displacement; running performance; microtechnology

1. Introduction

The assessment of match running, defined as the on-feet displacement covered by players, in rugby league has received much attention to date (Cummins et al., 2013). This is in part due to the advent of Global Positioning Systems (GPS), with integrated microtechnology, that has allowed practitioners to easily collect large volumes of automated positional and displacement data during matches. Displacement metrics are generally considered to be any variable describing a measure of distance, speed, or acceleration of a player, as defined in the previous literature (Polglaze et al., 2016). By definition, speed ($m{\cdot}s^{-1}$) and acceleration ($m{\cdot}s^{-2}$) are the first and second derivatives of distance, respectively, and as such both are functions of distance and time (Polglaze et al., 2016).

An understanding of the running demands that individual players have been exposed to and will encounter during upcoming matches has implications within the athlete monitoring and subsequent training prescription processes (Kelly & Coutts, 2007). Despite this, much of the previous literature has tended to focus upon only reporting displacement, which may lead to a 1-dimensional view of match running with little information regarding the generalisability of their findings (Bradley & Ade, 2018; Paul et al., 2015). As such, it is of interest to understand how the many different components combine to form the context within a match and subsequently contribute to explaining what causes an increase or decrease in an individual's displacement during matches. For example, from a team conditioning perspective, this type of information may inform the training microcycle, such as prescribing a tapering period prior to a match with an estimated high running performance, or vice versa. Lastly, understanding the context may also inform training so that it closely resembles match-play. However, large match-to-match variability previously observed within displacement metrics means that explaining match running, and ultimately providing accurate estimations of future match running is a challenging process (Kempton et al., 2015).

From a mechanistic perspective, match running may be explained as the proportional product of all of the available information about a match and would allow for this observed variability to be fully explained by a nearly infinite number of contextual factors (Paul et al., 2015). In this sense, a contextual factor is any variable which provides information about the state of the match at any given time, such as the scoreline, the positions of the players on

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the pitch, or the environmental conditions. However, the relationship between the various contextual factors and match running is complex, yet researchers have tended to rely on the general linear model to explain the factors that influence displacement. Importantly, taking this approach is somewhat reductionist, since it does not take into account the covariance in the data or indeed its complexity, and as such has considerable limitations (Balagué et al., 2017). Within a recent systematic review in soccer, the effects of situational (e.g. ball possession, scoreline, congested schedule) and environmental-related (e.g. temperature, altitude) contextual factors on match running were investigated (Trewin et al., 2017). The authors concluded that both types of contextual factors had the potential to influence match running performance, meaning that the inclusion of a single contextual factor is not appropriate and would provide a one-dimensional view of the match (Paul et al., 2015). Therefore, within a reductionist framework statistical models such as mixed effects models can be used to obtain the pure effect of a single contextual factor through simultaneously controlling for other factors. Clearly, it would not be possible to collect and account for all possible contextual factors, nor would it be useful since the final model would not be flexible enough to predict future match running due to model overfitting (Carey et al., 2018). Therefore, it might be more advantageous to take an orthogonal data analysis approach (Till et al., 2016), by determining the minimum number of uncorrelated variables that are still capable of capturing the information within the game (i.e. the concept of model parsimony (Coutts, 2014)), and which still provide an accurate estimation of future match running. A parsimonious model would not only increase interpretability, generalisability, and practical implementation of the model but would also remove statistical artefacts such as multicollinearity (Till et al., 2016; Weaving et al., 2019).

Previous reviews investigating match running in rugby league have focused primarily on only a small number of contextual factors but nonetheless have found differences between sub-samples such as competition standards, age grades and positional groups (Hausler et al., 2016; Johnston et al., 2014). It is likely that the contexts would differ markedly for each of these sub-samples, and it would therefore seem appropriate to examine them as independent groups. Within this systematic review, the sub-sample of interest was senior male professional rugby league players. Given the enormous breadth of potential factors that may influence displacement within rugby league matches, a systematic review that considers all possible variables currently identified by literature is warranted. Moreover, within previous systematic reviews, there was a lack of critical commentary on the data analytical methods used by included studies (Hausler et al., 2016; Johnston et al., 2014), such a commentary would be valuable given the complexity in the topic area. Therefore, the primary aim of this review was to: (1) systematically identify the specific environmental, individual, and task-related contextual factors that may affect professional senior male rugby league match running; and (2) to investigate the data analytical methods used by each study to assess the effect of each factor.

2. Methods

2.1. Search strategy

A systematic review was carried out in accordance with the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) statement (Moher et al., 2009). This systematic review was not pre-registered and is therefore exploratory. A search of electronic databases (Web of Science, Scopus, CINAHL, MEDLINE, SPORTDiscus, PubMed) was performed from the earliest record to October 2019. A Boolean search phrase was used to identify relevant original research articles, the exact searches for each database can be found in supplementary file 1. The following terms were included in each search:

(1) Rugby league: "rugby league" OR rugby OR "rugby football" OR "rugby player*" OR "rugby football player*"
(2) Match-play: running OR "match running demands" OR "match running performance" OR "match-play" OR "match play" OR "match demands" OR "match characteristics" OR "physical demands" OR "movement demands" OR "movement characteristics" OR "activity profiles"
(3) GPS: microtechnology OR "micro-technology" OR GPS OR "global positioning system"
(4) Contextual influences: influence OR effect OR affect OR explain OR compare OR difference OR impact OR covariate OR factor OR relationship OR context OR contextual OR situation OR situational OR environment OR environmental OR physical OR technical OR tactical
(5) 1. AND 2 AND 3 AND 4

2.2. Study selection

After removing duplicates, two of the authors (NDB, SW) independently reviewed the remaining records, which involved an initial title and abstract screening against the eligibility criteria. After which the same two authors checked the full texts of the remaining articles for verification, using the same eligibility criteria. Reference lists of the final-included articles were then checked to identify other potentially relevant studies. Any disagreements were resolved through discussion at all stages. The following eligibility criteria were used for inclusion:

- The article was original and peer reviewed.
- The article investigated the influence, effect, or association of at least one contextual factor on or with at least one measure of displacement.
- Displacement was quantified through GPS.
- Included competitive match-play.
- The sample included senior male rugby league players.

Contextual factors were defined as any variables related to the environment, individual, or task and contained two or more factor levels (e.g. (1) home; (2) away). Measures of displacement included distance (e.g. total distance, low-speed running [LSR] distance, moderate-speed running [MSR] distance, high-speed running [HSR] distance), speed (e.g. average speed, HSR speed, MSR speed, LSR speed), or acceleration metrics. Studies were included only if they used GPS, due to a known lack of agreement between measurement systems (Buchheit et al., 2014).

2.3. Data extraction

From the included studies, data relating to sample characteristics (positional groups, sample size, competition level), GPS specifications (brand, model, sampling frequency, software) and GPS signal quality (horizontal dilution of precision (HDOP), number of connected satellites) were extracted. Raw data was extracted from any displacement variables (mean ± SD) which were described by at least 2 levels of a contextual factor, as well as the statistical analyses used and the contextual factors themselves. Where necessary, an online graph digitiser (WebPlotDigitizer v4.1) was used to extract data only available in figures (Gabbett, 2012, 2013; Gabbett et al., 2014; Hulin et al., 2015; Murray et al., 2014; Waldron et al., 2013).

A hierarchical approach was followed in extracting the influence or effect of a contextual factor. Firstly, an effect size (ES) Cohen's d statistic was extracted for each contextual factor where pairwise comparisons between levels were reported. Other effect statistics (e.g. correlation effect size [r]) were converted to Cohen's d if possible, through the *psych* package in R Studio (version 3.4.2). This was given by:

$$d = \frac{2r}{\sqrt{1 - r^2}}$$

If the ES was not reported within the study, the means, standard deviations (SD), and sample size were used to calculate Cohen's d ES and 90% confidence intervals [CI] also using the *psych* package. This approach was used given the various statistical approaches adopted by several included studies, where in some studies the estimated effects of a variable may be moderated by other interacting independent variables included in the same analysis. Moreover, if the reported ES was derived from a model or test with a single independent variable (e.g. t-test), then the 90% CI was recalculated due to discrepancies found between reported and calculated CIs.

Given the exploratory nature of the review and upon extensive read-throughs of included articles, an inductive analytical approach (Thomas, 2006) was utilised to reduce the complexity in interpreting the breadth of included contextual factors. This *a posteriori* approach allowed for categories to emerge from the data.

2.4. Assessment of methodological quality

The methodological quality of all included studies was independently assessed by two authors (NDB and SW) using a modified version of the Downs & Black (1998) scale. The measurement tool itself has good test–retest reliability ($r = 0.88$) and inter-rater reliability ($r = 0.75$) and has been recommended as a suitable tool for systematic reviews (Deeks et al., 2003). Given the observational nature of match demand-related studies, and in accordance with previous systematic reviews (Hausler et al., 2016; Whitehead et al., 2018), only 11 relevant questions were included (questions 1–3, 6, 7, 10–12, 16, 18, 20). Additionally, question 10 was modified to include the reporting of ES (Downs & Black, 1998). Modified versions of the Downs and Black scale are widely used within the team-sports-related literature (Cummins et al., 2013; Hausler et al., 2016; Kloskowska et al., 2016; Silva et al., 2018; Whitehead et al., 2018), but have limitations nonetheless. For example, since all answers are dichotomous an equal weighting is given to all items, irrespective of importance.

2.5. Statistical analysis

A meta-analysis was precluded within this review due to heterogeneity identified in speed thresholds, GPS devices, statistical analyses, and contextual factor definitions. All data are presented as mean ± SD and ES with 90% confidence intervals (CI) where possible. Effect sizes were scaled against standardised thresholds of <0.20, 0.20–0.59, 0.60–1.19, 1.20–2.00, >2.00 corresponding to trivial, small, moderate and large, and very large effects, respectively (Hopkins et al., 2009). Forest plots were produced for contextual factors that logically grouped together, using the R package *"forestplot"*.

3. Results

The final electronic database search yielded 739 potential articles, with 1 other article identified from another source. After the removal of duplicates, title, abstract, and full-text screening, 15 studies remained for data extraction (Bradley et al., 2016; Cummins et al., 2018; Delaney et al., 2016; Evans et al., 2018; Gabbett, 2012, 2013; Gabbett et al., 2014, 2013; Hulin et al., 2015; Kempton & Coutts, 2016; Kempton et al., 2017; Murray et al., 2014; Quinn et al., 2015; Twist et al., 2014; Waldron et al., 2013). Figure 1 provides a schematic representation of excluded articles at each stage of the screening process.

3.1. Study characteristics

Descriptive characteristics of the 15 included studies are shown in Table 1. Twelve (80%) studies contained a single team (Bradley et al., 2016; Cummins et al., 2018; Delaney et al., 2016; Evans et al., 2018; Gabbett, 2012, 2013; Gabbett et al., 2014, 2013; Kempton & Coutts, 2016; Murray et al., 2014; Quinn et al., 2015; Waldron et al., 2013), whilst the remaining three studies (20%) contained 2 teams (Hulin et al., 2015; Kempton et al., 2017; Twist et al., 2014), totalling 18 teams from all samples. Of these 18 teams, 5 (28%) teams competed in the European Super League (ESL) (Bradley et al., 2016; Evans et al., 2018; Quinn et al., 2015; Twist et al., 2014; Waldron et al., 2013), whilst 13 (72%) teams competed in the National Rugby League (NRL) (Cummins et al., 2018; Delaney et al., 2016; Gabbett, 2012, 2013; Gabbett et al., 2014, 2013; Hulin et al., 2015; Kempton & Coutts, 2016; Kempton et al., 2017; Murray et al., 2014; Twist et al., 2014). All studies analysed competitive matches from the teams' respective domestic leagues, with one study including one match from the World Club Challenge (Quinn et al., 2015). Apart from Bradley et al. (2016) which utilised a quasi-experimental pre-post-test design, all other studies utilised prospective case series experimental designs (Cummins et al., 2018; Delaney et al., 2016; Evans et al., 2018; Gabbett, 2012, 2013; Gabbett et al., 2014, 2013; Hulin et al., 2015; Kempton & Coutts,

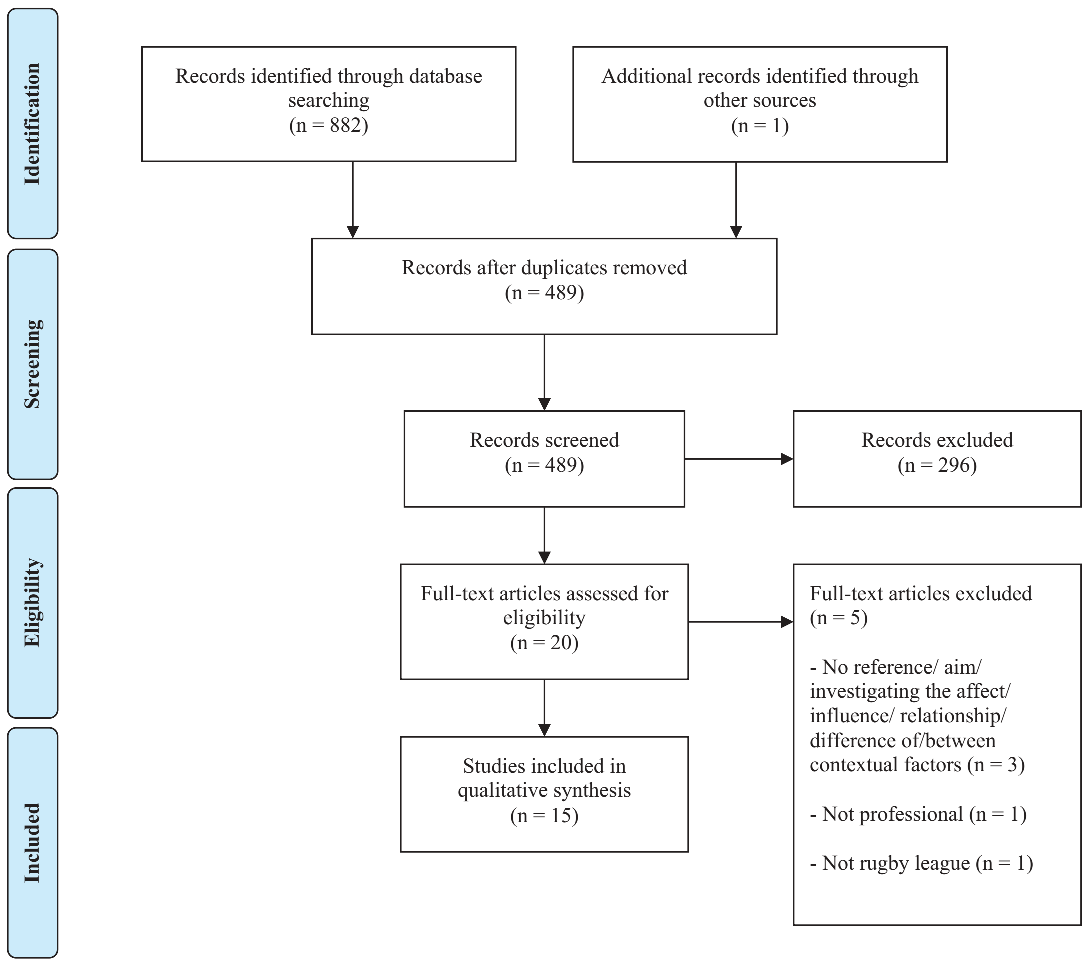

Figure 1. Flowchart of the search strategy according to PRISMA guidelines.

2016; Kempton et al., 2017; Murray et al., 2014; Quinn et al., 2015; Twist et al., 2014; Waldron et al., 2013).

Information regarding the GPS specifications, as well as speed and acceleration classifications used by each study, are described in Table 2. Regarding the GPS signal quality, 2 (13%) out of the 15 studies reported the mean ± SD HDOP, whilst 5 (33%) reported the mean ± SD number of connected satellites throughout their data collection period. Table 3 displays the methodological quality of all included studies. Scores ranged from 7 to 9, out of a total score of 11.

3.2. Influence of contextual factors on match running

Contextual factors were split into the following categories: individual characteristics, match result, team strength, opposition strength, match conditions, technical/tactical demands, spatial/temporal characteristics, and nutrition. The included contextual factors within each study are outlined in Table 4. Due to the breadth of results, not all pairwise comparisons are reported and so raw data from each study can be found in supplementary file 3.

3.2.1. Statistical and data analyses

The statistical and data analyses adopted by each study to investigate the influence of a contextual factor on a displacement variable are described in Table 5. All studies used univariate statistical analyses, meaning they only included one dependent variable. Specifically, single covariate models (e.g. t-tests) were used by five studies (33%) (Bradley et al., 2016; Gabbett et al., 2013, 2014; Gabbett, 2012, 2013), a linear mixed effects model was used by four studies (27%) (Cummins et al., 2018; Delaney et al., 2016; Kempton & Coutts, 2016; Kempton et al., 2017), whilst seven studies (47%) used variations of ANOVA (Evans et al., 2018; Gabbett et al., 2014; Hulin et al., 2015; Murray et al., 2014; Quinn et al., 2015; Twist et al., 2014; Waldron et al., 2013). Of the 15 included studies, 7 (47%) showed evidence of accounting for repeated measures within their statistical analyses (Cummins et al., 2018; Delaney et al., 2016; Evans et al., 2018; Kempton & Coutts, 2016; Kempton et al., 2017; Quinn et al., 2015; Twist et al., 2014).

3.2.2. Individual characteristics

The associations of cardiorespiratory and metabolic fitness qualities with displacement metrics were investigated by three studies in this review (Delaney et al., 2016; Gabbett et al., 2013; Kempton & Coutts, 2016), and was the only included contextual factor within the individual characteristics category. Effect sizes were all in the positive direction, indicating a higher fitness test score to be associated with large increases in

Table 1. Sample characteristics of final studies included in this review.

Study	Position (*n*); total sample (*n*)	Competitive level (*n* teams)	Competition analysed (season, matches analysed)	Wins	Losses	Draws	Final ladder position
Bradley et al. (2016)	Total (16)	ESL (1)	ESL (NR, 1)	NR	NR	NR	NR
Cummins et al. (2018)	Outside backs (4), adjustables (4), wide-running forwards (7), hit-up forwards (3); total (18)	NRL (1)	NRL (2013, NR)	NR	NR	NR	NR
Delaney et al. (2016)	Props and locks (14), hookers (4); total (18)	NRL (1)	NRL (2014, 24)	10	14	0	12
Evans et al. (2018)	Outside backs (6), pivots (5), middles (5), wide-running forwards (4); total (20)	ESL (1)	ESL (2012, 2013, 2014, 81)	2012: 6 2013: 10 2014: 13	2012: 21 2013: 15 2014: 13	2012: 0 2013: 2 2014: 1	2012: 14 2013: 10 2014: 8
Gabbett (2012)	Hit-up, wide-running forwards, adjustables, outside backs; total (37)	NRL (1)	NRL (NR, 16)	NR	NR	NR	NR
Gabbett (2013)	Total (22)	NRL (1)	NRL (NR, 16)	NR	NR	NR	NR
Gabbett et al. (2013)	Total (38)	NRL (1)	NRL (NR, 16)	NR	NR	NR	NR
Gabbett et al. (2014)	Hit-ups, wide-running forwards, hookers; total (22)	NRL (1)	NRL (NR, 23)	16	7	0	1
Hulin et al. (2015)	Adjustables, hit-up, outside back; total (31)	NRL (2)	Low success: NRL (2013, 10) High success: NRL (2013, 15)	Low success: 14 High success: 17	Low success: 10 High success: 7	Low success: 0 High success: 0	NR
Kempton & Coutts (2016)	Adjustables (6), outside backs (8), wide-running forwards (4); total (18)	NRL (1)	NRL (2010, 2011, 37)	2010: 7 2011: 5	2010: 11 2011: 14	NA	NR
Kempton et al. (2017)	Low success team: pivots (7), outside backs (6), wide-running forwards (8), hit-up (4); total (25)High success team: pivots (8), outside backs (7), wide-running forwards (8), hit-up (6); total (29)	NRL (2)	Low success: NRL (2012, 18) High success: NRL (2014, 24)	Low success: 4 High success: 15	Low success: 14 High success: 9	Low success: 0 High success: 0	Low success: 16 High success: 4
Murray et al. (2014)	Adjustables, hit-up forwards, outside backs; total (31)	NRL (1)	NRL (NR, 30)	NR	NR	NR	NR
Quinn et al. (2015)	Total (15)	ESL (1)	ESL (NR, 2)WCC (NR, 1)	ESL: 1	ESL: 1WCC: 1	0	NR
Twist et al. (2014)	Outside backs, adjustables, hit-up forwards; total (NR)	ESL (1), NRL (1)	ESL (2011, 25)NRL (2011, 25)	ESL: 50%NRL: 44%	ESL: 50%NRL: 56%	ESL: 0%NRL: 0%	NR
Waldron et al. (2013)	Whole-match players: wing (3), full-back (1), centre (2), scrum half (1); total (7)Interchanges: prop (3), second row (5), hookers (2), loose forward (1); total (11)	ESL (1)	ESL (NR, 14)	10	4	0	NR

NR Not reported, ESL European Super League, NRL National Rugby League, WCC World Club Challenge.

NR, Not reported; ESL, European Super League; NRL, National Rugby League; WCC, World Club Challenge.

Table 2. GPS specifications, signal quality, and speed- and acceleration classifications throughout data collection periods of included studies.

Study	Brand, model (sampling rate)	Software	HDOP (mean ± SD)	Connected satellites (mean ± SD)	Speed classification ($m \cdot s^{-1}$)	Acceleration classification ($m \cdot s^{-2}$)
Bradley et al. (2016)	Catapult, S5 (10 Hz)	NR	NR	NR	NA	NA
Cummins et al. (2018)	GPSports SPI-ProX (5 Hz)	Custom software	NR	NR	High (>5.00)	Moderate (<1.12) High (1.13–2.78) Very high (>5)
Delaney et al. (2016)	GPSports, SPI HPU (5 Hz)[a]	Team AMS	1.1 ± 0.1	8.3 ± 1.4	NA	NA
Evans et al. (2018)	2012/2013: GPSports SPi ProXII (5 Hz) 2013/2014: STATSports Viper (10 Hz)	NR	NR	2012: 8 ± 2 2013: 8 ± 2 2014: 8 ± 1	High (>5.00)	NA
Gabbett (2012)	Catapult, MinimaxX Team 2.5 (5 Hz)	Logan Plus	NR	NR	Very low (0.00–1.00) Low (1.00–3.00) Moderate (3.00–5.00) High (5.00–7.00) Very high (>7.00)	Mild (0.55–1.11) Moderate (1.12–2.78) Maximal (>2.78)
Gabbett (2013)	Catapult MinimaxX Team 2.5 (5 Hz)	NR	NR	NR	Low (0.00–5.00) High (5.00–7.00) Sprinting (>7.00)	NA
Gabbett et al. (2013)	Catapult MinimaxX Team 2.5 (5 Hz)	NR	NR	NR	Low (0.00–5.00) High (5.00–7.00) Sprinting (>7.00)	NA
Gabbett et al. (2014)	Catapult, MinimaxX S4 (10 Hz)	NR	NR	NR	Low (<5.00) High (>5.00)	NA
Hulin et al. (2015)	Catapult, MinimaxX S4 (10 Hz)	Sprint v5.1.0.1	NR	High success team: 12 ± 1 Low success team: 11 ± 2	Low (<5.00) High (>5.00)	NA
Kempton & Coutts (2016)	GPSports, SPI-ProX (5 Hz)	Team AMS vR1.2012.1	NR	8.9 ± 1.7	High (>4.00)	NA
Kempton et al. (2017)	GPSports, SPI-ProX (5 Hz)	Team AMS vR1.2014.11	NR	NR	Low (<4.00) High (4.00–5.28) Very high (5.28–6.39) Sprint (>6.39)	Acceleration (>2.78) Decelerations (<2.78)
Murray et al. (2014)	Catapult, MinimaxX Team 2.5 (5 Hz)	Team AMS v2.1	NR	NR	Low (0.00–3.00) Moderate (3.00–5.00) High (>5.00)	NA
Quinn et al. (2015)	GPSports, SPI-ProX (5 Hz)	NR	NR	NR	High (>5.00)	NA
Twist et al. (2014)	GPSports, SPI-Pro (5 Hz)	Team AMS v2.1	NR	NR	High (>4.00)	NA
Waldron et al. (2013)	GPSports, SPI-Pro (5 Hz)	Team AMS v2.1	1.2 ± 0.1	8 ± 1	High (>3.89)	NA

[a]Interpolated to 15 Hz, NR, Not reported; NA, Not applicable; HDOP, Horizontal dilution of precision.

Table 3. Methodological quality assessment of included studies (Downs & Black, 1998).

Study	Question number											Total
	1	2	3	6	7	10	11	12	16	18	20	
Bradley et al. (2016)	1	1	1	1	1	1	0	0	1	1	0	8
Cummins et al (2018)	1	1	1	1	1	1	0	0	1	1	1	9
Delaney et al. (2016)	1	1	1	1	1	1	0	0	1	1	1	9
Evans et al. (2018)	1	1	1	1	1	1	0	0	1	1	1	9
Gabbett (2012)	1	1	0	1	0	1	0	0	1	1	1	7
Gabbett (2013)	1	1	0	1	1	1	0	0	1	1	1	8
Gabbett et al. (2013)	1	1	0	1	1	1	0	0	1	1	1	8
Gabbett et al. (2014)	1	1	0	1	1	1	0	0	1	1	1	8
Hulin et al. (2015)	1	1	0	1	1	1	0	0	1	1	1	8
Kempton & Coutts (2016)	1	1	1	1	1	1	0	0	1	1	1	9
Kempton et al. (2017)	1	1	1	1	1	1	0	0	1	1	1	9
Murray et al. (2014)	1	1	0	1	1	1	0	0	1	1	1	8
Quinn et al. (2015)	1	1	1	1	1	1	0	0	1	1	0	8
Twist et al. (2014)	1	1	0	1	1	1	0	0	1	1	1	8
Waldron et al. (2013)	1	1	1	1	1	1	0	0	1	1	1	9

1 Yes, 0 No.

average speed (ES range = 1.19 to 1.46) (Delaney et al., 2016; Kempton & Coutts, 2016) and small to large increases in HSR speed (ES range = 0.11 to 1.54) (Gabbett et al., 2013; Kempton & Coutts, 2016). All changes in LSR speed were trivial (Gabbett et al., 2013) (Figure 2).

3.2.3. Match result

The effects of match result (win or loss) were investigated by four studies (Delaney et al., 2016; Kempton & Coutts, 2016; Murray et al., 2014; Gabbett, 2013) and are described in Figure 3. Murray et al. (2014) stratified analyses by a win or loss after a short (5–6 d), medium (7–8 d) or long (9–10 d) match turnaround. They found a small increase in average speed when the match was won after a short match turnaround (ES [90% CI] = 0.59 [0.02 to 1.19]), whereas medium and long turnarounds were trivial. Match result, defined by both win or loss and points differential, was found to be non-significant in a mixed model analysis by Delaney et al. (2016), and were dropped from the final models. Gabbett (2013) also defined winning and losing by points differential, i.e. a small (≤6 points), moderate (7–17 points), and large (≥18 points) win or loss. Displacement variables were highest during a large win or loss, including average speed (large win = 114.4 ± 47.1 m·min^{-1}, large loss = 101.9 ± 16.7 m·min^{-1}), LSR speed (large win = 108.9 ± 45.6 m·min^{-1}, large loss = 96.0 ± 16.1 m·min^{-1}), and HSR speed (large win = 5.5 ± 2.7 m·min^{-1}, large loss = 6.0 ± 2.3 m·min^{-1}). The lowest average speed (96.3 ± 14.9 m·min^{-1}) and HSR speed (4.6 ± 2.7 m·min^{-1}) were found during a moderate losing margin, whilst the lowest LSR speed was found during a small losing margin (91.6 ± 23.7 m·min^{-1}).

3.2.4. Team strength

The strength of the observed team in the sample was only investigated by two studies, both of which analysed differences in displacement metrics between a single successful team and a single less-successful team (Hulin et al., 2015; Kempton et al., 2017). Hulin et al. (2015) defined team success by the percentage of matches won by the end of the season, whereby the successful team had won 71% and the less-successful team had won 58%. They then utilised segmental analysis to compare the highest running periods (i.e. peak), whereby the match was split into 16 equal 5-min non-overlapping segments (Hulin et al., 2015). They found the successful team to have lower average speed during 5-min peak, subsequent (i.e. 5-min segment immediately following the peak), and mean segments (i.e. mean across all 5-min segments) for adjustables, hit-up forwards, and outside backs (ES range = 0.88 to 2.00) (Hulin et al., 2015).

Kempton et al. (2017) defined success according to wins and losses (successful team = 15 wins and 9 losses; less-successful team = 4 wins and 14 losses), points scored per game (mean ± SD; successful team = 21.1 ± 8.8; less-successful team = 18.2 ± 10.7), points conceded per game (mean ± SD; successful team = 17.8 ± 8.8; less-successful team = 29.3 ± 12.0), and final ladder position (successful team = 4th; less-successful team = 16th). They found trivial differences between successful and less-successful teams for total distance, average speed, LSR distance, LSR speed, and HSR distance (Kempton et al., 2017). The less-successful team in the same study achieved higher HSR speed, as well as higher very high HSR distance, very high HSR speed, sprint distance, and sprint speed (ES range = 0.20 to 0.49). Lastly, the successful team had a small to moderately higher total accelerations and decelerations, and accelerations and decelerations relative to playing time, compared to the less-successful team (ES range = 0.36 to 0.94) (Kempton et al., 2017).

3.2.5. Opposition strength

The influence of opposition strength was investigated by three studies (Delaney et al., 2016; Kempton & Coutts, 2016; Gabbett, 2013), and is detailed in Figure 4. Playing against stronger opposition, as defined by final ladder position, resulted in small increases in average speed (ES [90% CI] = 0.39 [0.18 to 0.58]) (Delaney et al., 2016) and accelerations relative to playing time (ES [90% CI] = 0.21 [–0.5 to 0.91]) (Gabbett, 2013). Conversely, playing against weaker opposition was associated with small increases in total distance (ES [90% CI] = 0.30 [–0.41 to 1.00]) and HSR distance (ES [90% CI] = 0.58 [–0.14 to 1.29]) (Gabbett, 2013), along with a moderate increase in HSR speed (ES range = 0.58 to 0.60) (Kempton & Coutts, 2016; Gabbett, 2013). Delaney et al. (2016) also defined opposition strength by recent form (wins in last 5 matches) and found poorer form to be associated with increased average speed (ES [90% CI] = 0.24 [0.04 to 0.45]).

3.2.6. Match conditions

Match conditions comprised within season phase (Figure 5), between season comparison, match turnaround (Figure 6), and match location. The associations of season phase (e.g. early-season, mid-season, late-season) were varied with average speed (ES range = –0.49 to 0.77) (Delaney et al., 2016; Kempton & Coutts, 2016; Twist et al., 2014), HSR speed (ES range = –0.37 to 0.77) (Kempton & Coutts, 2016; Twist et al., 2014), MSR speed (ES range = –0.59 to 0.25) (Twist et al., 2014), and LSR speed (ES range = –0.23 to 0.29) (Twist et al., 2014).

Evans et al. (2018) explored changes in displacement between 3 consecutive seasons (2012, 2013, and 2014). For average speed, they found a mean large increase across positions from 2012 to 2013 (mean ± SD = 87.0 ± 2.4 *vs* 91.3 ± 3.0; ES [90% CI] = 1.60 [0.73 to 2.43]) and 2013 to 2014 (mean ± SD = 87.0 ± 2.4 *vs* 96.6 ± 2.4; ES [90% CI] = 2.00 [1.06

Table 4. Contextual factors included within each study.

Author	Individual characteristics	Match result	Team strength	Opposition strength	Match conditions	Technical/tactical demands	Spatial/temporal characteristics	Nutrition
Bradley et al. (2016)	X	X	X	X	X	X	First half, second half	High CHO, low CHO
Cummins et al. (2018)	X	X	X	X	X	Interchange, whole match	X	X
Delaney et al. (2016)	Fitness (IFT score)	Win/loss, points differential	X	Wins last 5, final ladder position	Season phase, location, match turnaround	Tackles made, tackles received	Bout duration, time in possession, ball-out-play time	X
Evans et al. (2018)	X	X	X	X	Season	X	X	X
Gabbett (2012)	X	X	X	X	X	Sprinting with/ without ball	X	X
Gabbett (2013)	X	Win/loss, points differential	X	Final ladder position	X	X	X	X
Gabbett et al. (2013)	High/low fitness (PHIIRA/RSA/MAP)	X	X	X	X	X	X	X
Gabbett et al. (2014)	X	X	X	X	X	Attack, defence	Field position	X
Hulin et al. (2015)	X	X	Final ladder position	X	X	X	16 equal periods	X
Kempton & Coutts (2016)	Fitness (1.2 km shuttle run)	Win/loss	X	Final ladder position	Season phase, location, match turnaround	Tackles made	Ball-out-play time, number of possessions	X
Kempton et al. (2017)	X	X	Final ladder position	X	X	X	X	X
Murray et al. (2014)	X	Win/loss	X	X	Match turnaround	X	X	X
Quinn et al. (2015)	X	X	X	X	Location, competition (ESL vs. WCC)	X	X	X
Twist et al. (2014)	X	X	X	X	Season phase, competition (ESL vs. NRL)	X	First half, second half	X
Waldron et al. (2013)	X	X	X	X	X	Interchange bout	4 equal periods	X

X No relevant contextual factor included within study, CHO Carbohydrate, ES Effect size, IFT Intermittent fitness test, PHIIRA Prolonged high-intensity intermittent running ability, RSA Repeated sprint ability, MAP Maximal aerobic power, RM Repeated measures, ESL European Super League, NRL National Rugby League.

X, No relevant contextual factor included within study; CHO, Carbohydrate; ES, Effect size; IFT, Intermittent fitness test; PHIIRA, Prolonged high-intensity intermittent running ability; RSA, Repeated sprint ability; MAP, Maximal aerobic power; RM, Repeated measures; ESL, European Super League; NRL, National Rugby League.

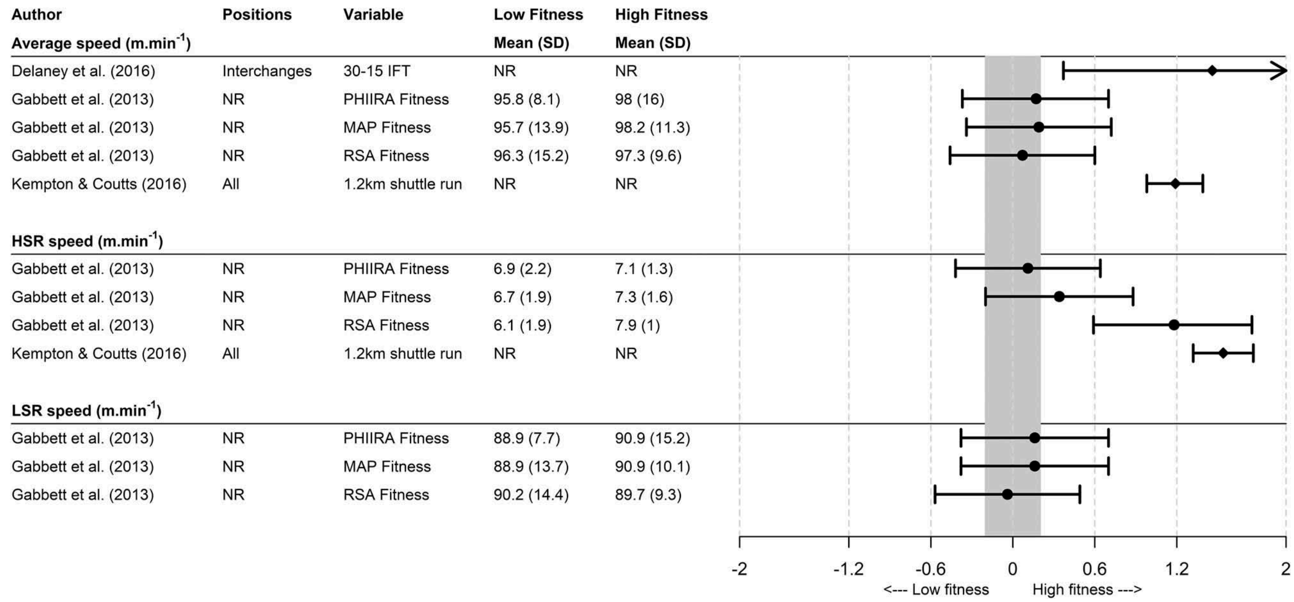

Figure 2. Forest plot of the effect of fitness on displacement variables, including mean ± SD, with Cohen's *d* ES differences. For Delaney et al. (Quinn et al., 2015), the upper 90% confidence interval was clipped to retain the resolution of the X-axis. *Circles* represent unadjusted contextual factors, *diamonds* represent adjusted contextual factors.

to 2.89]), with a very large increase observed from 2012 to 2014 (ES [90% CI] = 4.00 [2.65 to 5.29]). A similar trend was observed for HSR speeds, with large increases found for 2012 to 2013 (mean ± SD = 6.3 ± 1.3 *vs* 7.4 ± 0.9; ES [90% CI] = 0.90 [0.11 to 1.66]), 2013 to 2014 (mean ± SD = 7.4 ± 0.9 *vs* 8.1 ± 0.5; ES [90% CI] = 1.10 [0.29 to 1.88]), as well as from 2012 to 2014 (ES [90% CI] = 2.00 [1.06 to 2.89]).

Delaney et al. (2016) and Murray et al. (2014) found the majority of non-trivial effects of match turnaround on displacement metrics were negative, meaning they increased during

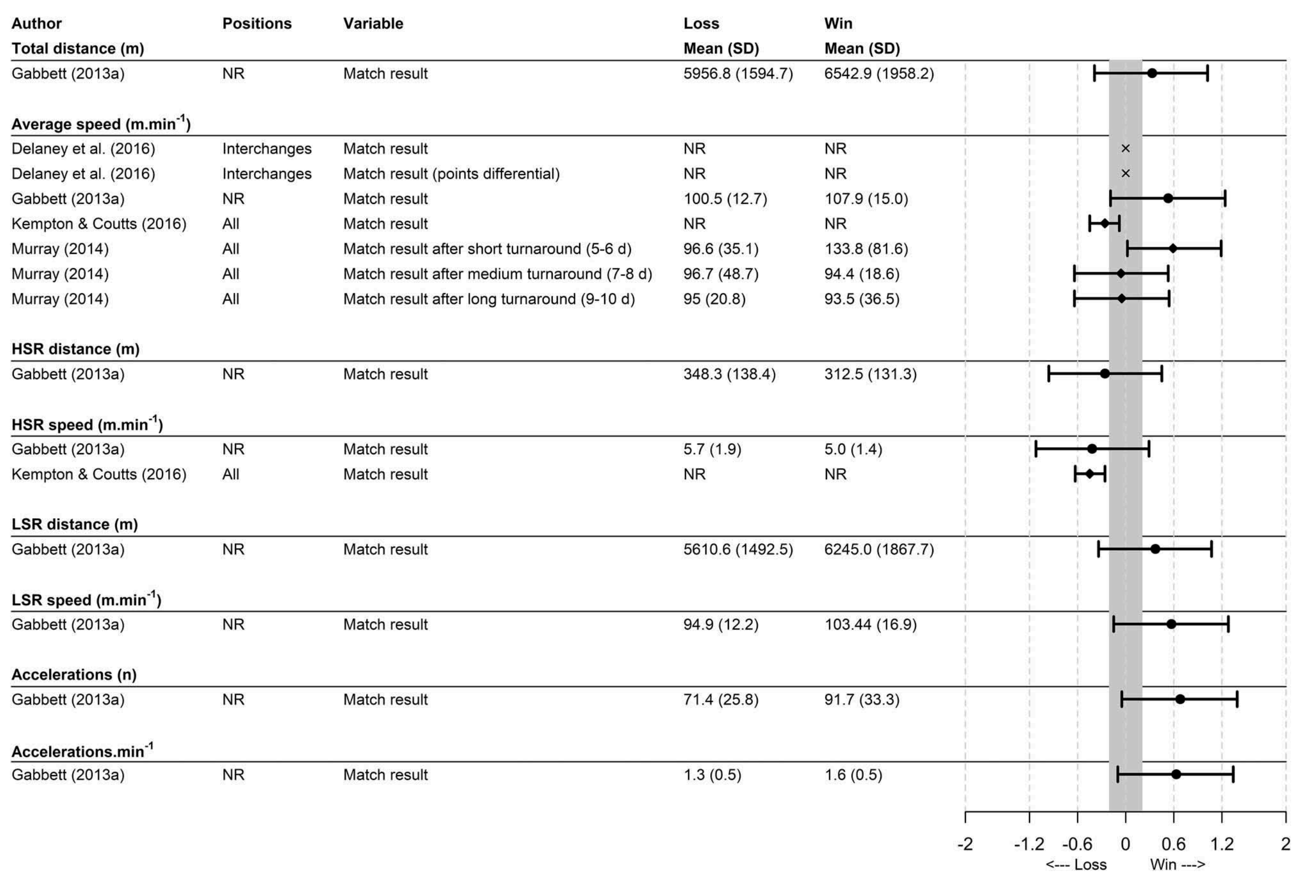

Figure 3. Forest plot of the effect of match result on displacement variables, including mean ± SD, with Cohen's *d* ES differences. *Circles* represent unadjusted contextual factors, *diamonds* represent adjusted contextual factors, *crosses* represent a non-significant effect.

Table 5. Statistical analyses and number of independent variables included in models.

Study	Data analyses	Repeated measures	Independent variables (n)
Bradley et al. (2016)	t-test	Yes	2
Cummins et al. (2018)	First order autoregressive linear mixed effects model	Yes	1
Delaney et al. (2016)	Linear mixed effect model	Yes	13
Evans et al. (2018)	RM ANOVA	Yes	1
Gabbett (2012)	Cohen's *d* ES differences	Yes	1
Gabbett (2013)	Cohen's *d* ES differences	Yes	3
Gabbett et al. (2013)	Cohen's *d* ES differences	Yes	3
Gabbett et al. (2014)	t-test (overall attack v defence); One-way ANOVA (field position)	Yes	2
Hulin et al. (2015)	Factorial ANOVA (team strength x period)	Yes	3
Kempton & Coutts (2016)	Linear mixed effect model	Yes	9
Kempton et al. (2017)	Linear mixed effect model	Yes	1
Murray et al. (2014)	Two separate factorial ANOVA (position x recovery length; result x recovery length)	Yes	3
Quinn et al. (2015)	One-way RM ANOVA	Yes	2
Twist et al. (2014)	Factorial ANOVA (competition x position); Factorial RM ANOVA (competition x half); MANOVA (competition x season phase)	Yes	4
Waldron et al. (2013)	Factorial ANOVA (bout type x match quartile)	Yes	2

ES, Effect size; RM, Repeated measures.

shorter turnarounds (ES range = −0.22 to −1.27). Conversely, Kempton & Coutts, (2016) found increases in average speed (ES [90% CI] = 0.24 [0.06 to 0.43]) and HSR speed (ES [90% CI] = 0.22 [0.04 to 0.41]) during longer turnarounds.

The effects of match location (i.e. home or away) on average speed were varied, whereby Delaney et al. (2016) found a non-significant effect, and Kempton & Coutts (2016) found a moderate increase when playing away compared to home (ES [90% CI] = 0.65 [0.47 to 0.84]). The latter study also found a moderate increase in HSR speed when playing away (ES [90% CI] = 0.74 [0.56 to 0.92]). Quinn et al. (2015) compared 2 domestic ESL matches with an away World Club Challenge – match in Australia. In absolute terms, they found large increases in HSR distance, number of sprints, number of accelerations, and number of decelerations when playing in Australia (ES range = 1.50 to 2.45). Relative to ball-in-play time, large increases in the number of sprints, number of accelerations and number of decelerations were found (ES range = 1.57 to 1.77). Lastly, relative to playing time, playing in Australia resulted in large increases in the number of sprints, number of accelerations, and number of decelerations (ES range = 1.47 to 2.45).

3.2.7. Technical/tactical Demands

Four studies investigated associations of technical or tactical demands within match-play (Delaney et al., 2016; Gabbett et al., 2014; Kempton & Coutts, 2016; Gabbett, 2012). Gabbett et al. (2014) found large increases whilst defending *vs* attacking for both average speed (mean ± SD = 109.0 ± 16.0 *vs* 82.0 ± 12.0; ES [90% CI] = 1.35 [0.55 to 2.12]) and LSR speed (mean ± SD = 104 ± 15 *vs* 78 ± 11; ES [90% CI] = 1.41 [0.60 to 2.19]). HSR speed also increased whilst in defence, but the effect was only small (mean ± SD = 5.3 ± 3.7 *vs* 3.9 ± 3; ES [90% CI] = 0.39 [−0.32 to 1.09]). Another study found 78.7% of total sprint efforts were completed with ball-in-hand (ES [90% CI] = 6.00 [4.68 to 7.27]) (TJ. Gabbett, 2012). Two studies explored associations of tackling with average speed (Delaney et al., 2016; Kempton & Coutts, 2016). Delaney et al. (2016) partitioned tackles into tackles made and tackles received, both of which

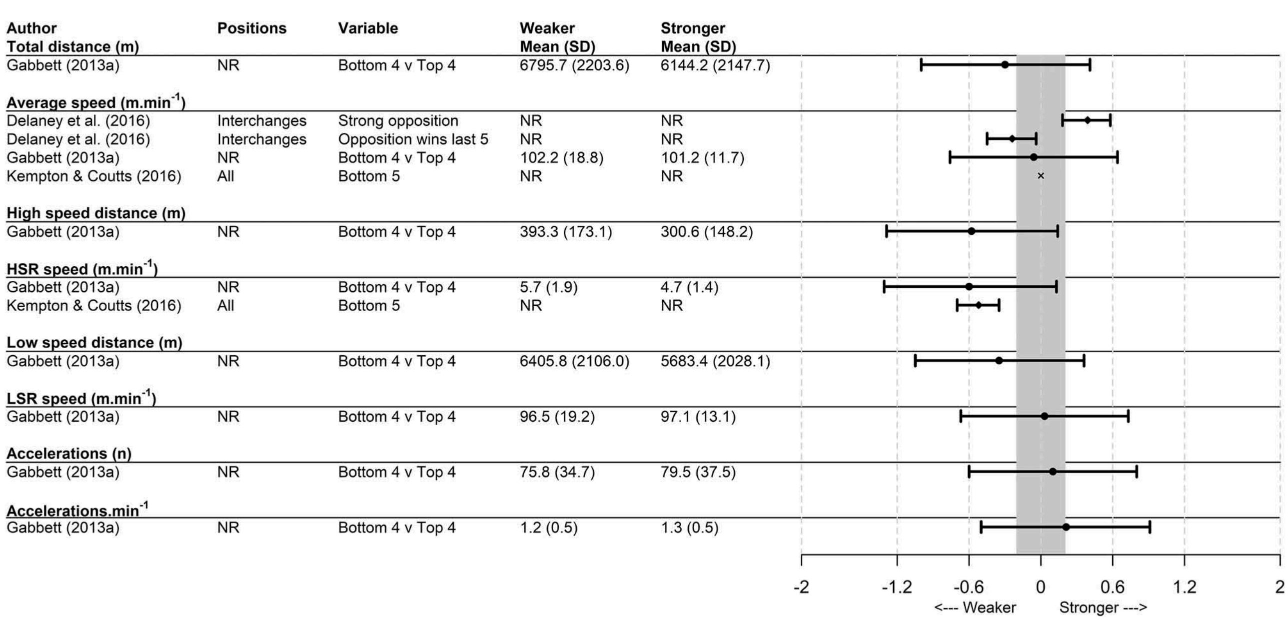

Figure 4. Forest plot of the effect of opposition strength on displacement variables, including mean ± SD, with Cohen's *d* ES differences. *Circles* represent unadjusted contextual factors, *diamonds* represent adjusted contextual factors, *crosses* represent a non-significant effect.

Author	Positions	Variable	Early season Mean (SD)	Mid season Mean (SD)	Late season Mean (SD)
Average speed (m.min^{-1})					
Delaney et al. (2016)	Interchanges	Mid season	NR	NR	NR
Delaney et al. (2016)	Interchanges	Late season	NR	NR	NR
Kempton & Coutts (2016)	All	Early season	NR	NR	NR
Twist et al. (2014)	All (ESL)	Early v mid season	91.9 (18.0)	95.6 (13.3)	
Twist et al. (2014)	All (NRL)	Early v mid season	91.4 (8.0)	91.5 (9.0)	
Twist et al. (2014)	All (ESL)	Early v late season	95.0 (20.8)		98.2 (21.9)
Twist et al. (2014)	All (NRL)	Early v late season	91.4 (8.0)		87.6 (7.6)
Twist et al. (2014)	All (ESL)	Mid v late season		95.6 (13.3)	98.2 (21.9)
Twist et al. (2014)	All (NRL)	Mid v late season		91.5 (9.0)	87.6 (7.6)
HSR speed (m.min^{-1})					
Kempton & Coutts (2016)	All	Early season	NR	NR	NR
Twist et al. (2014)	All (ESL)	Early v mid season	6.0 (1.6)	5.9 (1.6)	
Twist et al. (2014)	All (NRL)	Early v mid season	7.2 (2.3)	7.6 (2.5)	
Twist et al. (2014)	All (ESL)	Early v late season	6.0 (1.6)		6.2 (1.9)
Twist et al. (2014)	All (NRL)	Early v late season	7.2 (2.3)		6.7 (2.4)
Twist et al. (2014)	All (ESL)	Mid v late season		5.9 (1.6)	6.2 (1.9)
Twist et al. (2014)	All (NRL)	Mid v late season		7.6 (2.5)	6.7 (2.4)
MSR speed (m.min^{-1})					
Twist et al. (2014)	All (ESL)	Early v mid season	13.5 (4.1	14.4 (3.1)	
Twist et al. (2014)	All (NRL)	Early v mid season	13.1 (3.4)	13.0 (3.7)	
Twist et al. (2014)	All (ESL)	Early v late season	13.5 (4.1		14.6 (4.1)
Twist et al. (2014)	All (NRL)	Early v late season	13.1 (3.4)		11.3 (2.6)
Twist et al. (2014)	All (ESL)	Mid v late season		14.4 (3.1)	14.6 (4.1)
Twist et al. (2014)	All (NRL)	Mid v late season		13.0 (3.7)	11.3 (2.6)
LSR speed (m.min^{-1})					
Twist et al. (2014)	All (ESL)	Early v mid season	72.4 (14.1)	75.2 (14.1)	
Twist et al. (2014)	All (NRL)	Early v mid season	70.7 (4.4)	70.5 (5.4)	
Twist et al. (2014)	All (ESL)	Early v late season	72.4 (14.1)		77.4 (19.4)
Twist et al. (2014)	All (NRL)	Early v late season	70.7 (4.4)		69.6 (5.1)
Twist et al. (2014)	All (ESL)	Mid v late season		75.2 (14.1)	77.4 (19.4)
Twist et al. (2014)	All (NRL)	Mid v late season		70.5 (5.4)	69.6 (5.1)

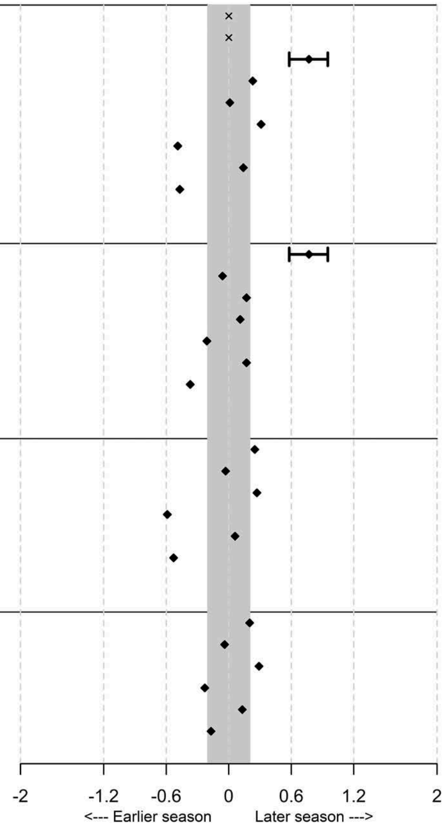

Figure 5. Forest plot of the effect of season phase on displacement variables, including mean ± SD, with Cohen's *d* ES differences. *Circles* represent unadjusted contextual factors, *diamonds* represent adjusted contextual factors, *crosses* represent a non-significant effect.

were found to increase average speed for interchange players (ES [90% CI] = 0.60 [0.40 to 0.82], 0.38 [0.18 to 0.58]). In contrast to this, Kempton & Coutts (2016) found an increase in total tackles made to reduce both average speed (ES [90% CI] = 0.20 [0.00 to 0.40]) and HSR speed (ES [90% CI] = 0.87 [0.40 to 1.96]) for all positions. For the same study, the individual number of attacking involvements had no significant effect within their models.

The differences in match running between interchanges and whole-match players were investigated by two studies (Cummins et al., 2018; Waldron et al., 2013). Cummins et al. (2018) analysed differences in interchange versus whole-match adjustables (hooker, half-back, five-eighth) and wide-running forwards (second-row, lock). For adjustables, small to very large decreases were seen when comparing whole-match versus interchanges for total distance, HSR speed, moderate accelerations, and moderate decelerations (ES range = 0.57 to 2.18). Conversely, small increases were seen for very high accelerations and very high decelerations (ES range = 0.25 to 0.45), whilst average speed and high-intensity accelerations and decelerations were all trivial. For wide-running forwards, when comparing whole-match versus interchanges small to moderate increases were seen for average speed, HSR speed, high-intensity accelerations and decelerations per minute, and very high-intensity accelerations and decelerations per minute (ES range = 0.31 to 0.65). Additionally, there was a very large reduction in total distance (ES [90% CI] = 2.24 [1.73 to 2.75]), whilst moderate-intensity accelerations and decelerations were trivial. Waldron et al. (2013) analysed matches by quartiles and subsequently split their sample into whole-match players, interchange players within their first bout, and interchange players within their second bout. For whole match players, as the match progressed there were successive small to moderate decreases in each quartile for both average speed (ES range = 0.22 to 0.75) and HSR speed (ES range = 0.53 to 0.92). For interchanges in their first bout, moderate decreases were seen for successive quartiles for average speed (ES range = 0.78 to 0.94) and HSR speed (ES range = 0.61 to 0.67), apart from a trivial change in quartile 2 to 3 for both variables.

3.2.8. *Spatial/temporal characteristics*

In one study, the influence of interchange bout duration (ES [90% CI] = 0.58 [0.38 to 0.79]), time in possession (ES [90% CI] = 0.42 [0.24 to 0.65]), and time out-of-play (ES [90% CI] = 0.49 [0.28 to 0.69]) were all associated with small reductions in average speed (Delaney et al., 2016). Likewise, ball out-of-play time was also associated with a moderate reduction in average speed (ES [90% CI] = 0.67 [0.49 to 0.87]) in another study; however, no significant effect was found for HSR speed (Kempton & Coutts, 2016). Gabbett et al. (2014) investigated the influence of field position on displacement metrics. The greatest average speed (relative to ball-in-play time) was covered whilst defending in the opposition's final third (i.e. opposition's dead ball line to 70 m line, mean ± SD = 118.1 ± 23.2 m·min^{-1}),

Author	Positions	Variable	Short turnaround Mean (SD)	Medium turnaround Mean (SD)	Long turnaround Mean (SD)
Total distance (m)					
Murray et al. (2014)	All	Short v medium turnaround	6796.0 (4605.5)	5618.0 (1559.0)	
Murray et al. (2014)	All	Short v late turnaround	6796.0 (4605.5)		6041.0 (2177.0)
Murray et al. (2014)	All	Medium v late turnaround		5618.0 (1559.0)	6041.0 (2177.0)
Average speed (m.min^{-1})					
Delaney et al. (2016)	Interchanges	Short turnaround	NR	NR	NR
Kempton & Coutts (2016)	All	Short turnaround	NR	NR	NR
Murray et al. (2014)	All	Short v medium turnaround	114.0 (33.4)	94.0 (11.1)	
Murray et al. (2014)	All	Short v late turnaround	114.0 (33.4)		95.0 (11.1)
Murray et al. (2014)	All	Medium v late turnaround		94.0 (11.1)	95.0 (11.1)
High speed distance (m)					
Murray et al. (2014)	All	Short v medium turnaround	467.0 (300.7)	434.0 (161.5)	
Murray et al. (2014)	All	Short v late turnaround	467.0 (300.7)		456.0 (206.0)
Murray et al. (2014)	All	Medium v late turnaround		434.0 (161.5)	456.0 (206.0)
HSR speed (m.min^{-1})					
Kempton & Coutts (2016)	All	Short turnaround	NR	NR	NR
Murray et al. (2014)	All	Short v medium turnaround	8.0 (2.2)	7.0 (1.7)	
Murray et al. (2014)	All	Short v late turnaround	8.0 (2.2)		7.0 (1.7)
Murray et al. (2014)	All	Medium v late turnaround		7.0 (1.7)	7.0 (1.7)
Moderate speed distance (m)					
Murray et al. (2014)	All	Short v medium turnaround	1420.0 (762.8)	1376.0 (328.5)	
Murray et al. (2014)	All	Short v late turnaround	1420.0 (762.8)		1526.0 (584.6)
Murray et al. (2014)	All	Medium v late turnaround		1376.0 (328.5)	1526.0 (584.6)
MSR speed (m.min^{-1})					
Murray et al. (2014)	All	Short v medium turnaround	25.0 (11.1)	24.0 (5.6)	
Murray et al. (2014)	All	Short v late turnaround	25.0 (11.1)		24.0 (5.6)
Murray et al. (2014)	All	Medium v late turnaround		24.0 (5.6)	24.0 (5.6)
Low speed distance (m)					
Murray et al. (2014)	All	Short v medium turnaround	4908.0 (3702.6)	3808.0 (1185.9)	
Murray et al. (2014)	All	Short v late turnaround	4908.0 (3702.6)		4059.0 (1520.0)
Murray et al. (2014)	All	Medium v late turnaround		3808.0 (1185.9)	4059.0 (1520.0)
LSR speed (m.min^{-1})					
Murray et al. (2014)	All	Short v medium turnaround	81.0 (33.4)	63.0 (5.6)	
Murray et al. (2014)	All	Short v late turnaround	81.0 (33.4)		77.4 (19.4)
Murray et al. (2014)	All	Medium v late turnaround		63.0 (5.6)	77.4 (19.4)

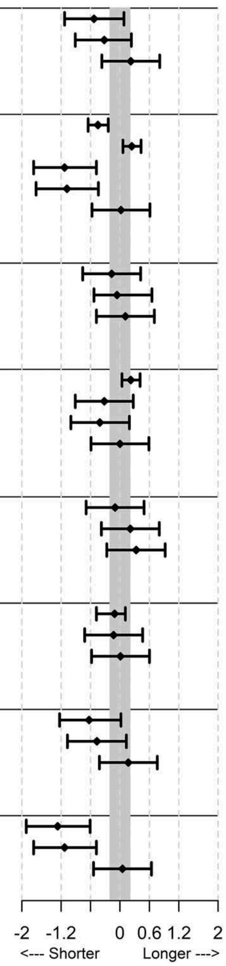

Figure 6. Forest plot of the effect of match turnaround on displacement variables, including mean ± SD, with Cohen's *d* ES differences. *Circles* represent unadjusted contextual factors, *diamonds* represent adjusted contextual factors.

which was the same for HSR speed (mean ± SD = 13.7 ± 11.1 m·min^{-1}). The greatest LSR speeds covered were during defensive phases in the middle third of the pitch (i.e. 31 m to 70 m line; mean ± SD = 105.5 ± 16.1 m·min^{-1}), and the opposition's third (mean ± SD = 104.4 ± 17.8 m·min^{-1}), of which the difference was trivial. Conversely, average speed (mean ± SD = 73.2 ± 14.8 m·min^{-1}), HSR speed (mean ± SD = 1.7 ± 2.4 m·min^{-1}), and LSR speed (mean ± SD = 72.0 ± 13.6 m·min^{-1}) were all lowest whilst attacking in the first third of the pitch (i.e. own dead-ball line to 30 m line).

3.2.9. Nutrition

Only one study looked at the influence of any nutritional-related contextual factor on displacement metrics within match-play (Bradley et al., 2016). Sixteen ESL players were split into 2 dietary groups and adhered to either a high (~6 g·kg $^{-1}$·day^{-1}) or low (~3 g·kg $^{-1}$·day^{-1}) carbohydrate diet for 36 h before kick-off. For a single competitive ESL match, small increases were found between high *vs* low carbohydrate groups for average speed (ES [90% CI] = 0.22 [−0.41 to 0.85]), small decreases were found for HSR speed (ES [90% CI] = −0.31 [−0.89 to 0.27]), whereas a trivial difference was found for LSR speed (ES [90% CI] = −0.13 [−0.93 to 0.67]) (Bradley et al., 2016). It must be noted that differences in muscle glycogen availability were unclear between high and low carbohydrate conditions for both pre- (449 ± 51 *vs* 444 ± 81 mmol per kg of dry weight) and post-match (243 ± 43 *vs* 298 ± 130).

4. Discussion

Understanding the relative importance of various contextual factors on running performance during competition is a crucial part of understanding the demands players are exposed to, which should then form the basis of any programme. This systematic review identified logical combinations of several contextual factors influencing match running demands, investigated by 15 original articles within professional senior male rugby league competition. Included studies found varying effects of contextual factors relating to individual characteristics (Delaney et al., 2016; Gabbett et al., 2013; Kempton & Coutts, 2016), match result (Delaney et al., 2016; Kempton & Coutts, 2016; Murray et al., 2014; Gabbett, 2013), match conditions (Delaney et al., 2016; Kempton & Coutts, 2016; Murray et al., 2014; Quinn et al., 2015; Twist et al., 2014), team strength (Hulin et al., 2015; Kempton et al., 2017), opposition strength (Delaney et al., 2016; Kempton & Coutts, 2016; Gabbett, 2013), technical/tactical demands (Delaney et al., 2016; Gabbett et al., 2014;

Kempton & Coutts, 2016; Gabbett, 2012), spatial/temporal characteristics (Bradley et al., 2016; Delaney et al., 2016; Gabbett et al., 2014; Hulin et al., 2015; Kempton & Coutts, 2016; Twist et al., 2014) and nutrition (Bradley et al., 2016). The majority of samples included came from the NRL competition (72%), with 28% from the ESL competition, and consisted of only a single team (80%) or 2 teams (20%).

4.1. Influence of individual characteristics on match running

Rugby league players require a range of physical characteristics to augment performance (Gabbett et al., 2008; Johnston et al., 2014; Till et al., 2016) given the multitude of intense bouts of exercise they must engage in including accelerations, changes-of-direction, sprints (Delaney, Duthie et al., 2016; Gabbett, 2012), collisions and wrestling activity (Cummins & Orr, 2015). However, the only identified physical quality relating specifically to match running demands was cardiorespiratory and metabolic fitness. Its substantially positive effects on average speed (Delaney et al., 2016; Kempton & Coutts, 2016) and HSR speed (Gabbett et al., 2013; Kempton & Coutts, 2016) were a consistent finding in this systematic review and agrees with research in other elite team sports such as soccer (Buchheit et al., 2010), rugby union (Cunningham et al., 2018; Smart et al., 2014; Swaby et al., 2016), and Australian Rules Football (Dillon et al., 2018; Mooney et al., 2011; Ryan et al., 2017). Whilst task failure and volitional exhaustion rarely occur within rugby league, players are still likely to perform high-intensity actions within the non-steady state exercise domains (i.e. heavy and severe intensities) (Jones & Vanhatalo, 2017), and as such will accumulate central (e.g. reduced motor neurone gain) and peripheral (e.g. metabolite accumulation and glycogen depletion) fatigue (Burnley & Jones, 2018). Therefore, a well-developed aerobic base will allow for quicker recovery between bouts, thereby permitting work rates to be maintained or increased in subsequent bouts (Tomlin & Wenger, 2001). It must be recognised that cardiorespiratory and metabolic qualities are also variable constructs and are affected by a number of factors (Booth et al., 2018), principally relating to fatigue status (Thorpe et al., 2017), training load accumulation (Bourdon et al., 2017), illness (Bourdon et al., 2017), or motivation (Vetter & Symonds, 2010). Baseline testing scores from the preseason may therefore not be representative of an individual's fitness qualities for matches later in the season, and thus would not be appropriate to model. Though regular maximal fitness tests are unfeasible and inappropriate during the in-season, new methods such as monitoring heart rate (Scott et al., 2018) and neuromuscular (Garrett et al., 2019) responses during standardised sub-maximal runs or small-sided games (Lacome et al., 2018b; Lacome et al., 2018a, 2018b) may provide suitable and valid alternatives.

4.2. Influence of match result on match running

Whilst there were substantial differences in displacement metrics found between levels of contextual factors relating to match result (win *vs* loss (Delaney et al., 2016; Kempton & Coutts, 2016; Murray et al., 2014; Gabbett, 2013) and points differential (Delaney et al., 2016; Gabbett, 2013), these findings were inconsistent both within and between studies. For example, the effect of winning on average speed had no effect in one study (Delaney et al., 2016), decreased in another (Kempton & Coutts, 2016), and increased in the remaining two studies (Murray et al., 2014; Gabbett, 2013). These inconsistencies could be due to a combination of several different factors which may be nested within the end match result, some of which may include playing style, player availability, score margin, strength of the opposition, or time in attack versus defence. However, the end result does not capture the evolving nature of the scoreline during the match itself (Lago-Peñas & Gómez-López, 2014), nor can it be considered a causal effect. In fact, many of the analysed contextual factors are not direct causes of displacement but are generally associative factors which will contain a greater proportion of the actual underlying causal mechanisms. A causal relationship ($X \rightarrow Y$) signifies X must always precede Y, such that there is a direct coupling of explanatory and dependent variables (Pearl, 2000). It would therefore be impossible to win or lose a match and then for running to occur, this is an example of reverse causality ($Y \rightarrow X$), since running occurs first and the match result is subsequently determined. To visualise this concept of causality, directed acyclic graphs (DAGs) have been previously utilised, particularly in epidemiological research (e.g. the obesity paradox (Banack & Kaufman, 2014). Such graphs are important tools to help practitioners and researchers develop a framework for selecting variables which either are or represent the underlying mechanisms for a given phenomenon, such as match running. It may therefore be more appropriate to model the scoreline during the game. The concept of causality direction will be discussed further in Section 4.7.

4.3. Influence of team and opposition strength on match running

Both the strength of the opposition (Delaney et al., 2016; Kempton & Coutts, 2016; Gabbett, 2013) and the strength of the observed team (Hulin et al., 2015; Kempton et al., 2017) have been considered in the current literature. There appeared to be a tendency for successful teams, defined by final ladder position, to run less especially at higher intensities (Hulin et al., 2015; Kempton et al., 2017). For opposition strength, also defined by final ladder position, playing against weaker opponents generally resulted in increased displacement (Kempton & Coutts, 2016; Gabbett, 2013). It would seem logical that the effects of team success, opposition strength, and match result would agree. However, differences in definitions between studies may contribute somewhat to the variability observed in the effects of each contextual factor. For example, the strength of a team is difficult to define since it will encompass a multitude of interacting factors. The strength of the team could also be defined by final ladder position, however, similarly to the end match result, this is an example of reverse causality. As such, Delaney et al. (2016) also attempted to capture the team's form by including the amount of wins in the previous 5 matches relative to the date of the fixture. Using this definition, they found that average speed actually increased when facing weaker opponents (i.e. less wins), where the opposite was found when strength was defined by final ladder position. This could indicate that the final ladder position may not reflect the state of the opposition at the time of the fixture. For example, the team could have suffered from a run of losses, incurred a number of injuries, or had a change in backroom staff.

4.4. Influence of match conditions on match running

Unlike match result, match conditions refer to situational factors which precede competition. The effects of match location were varied between studies whereby no significant effect was found in one study (Delaney et al., 2016), and a reduction in average speed and HSR speed when playing away was found in the other (Kempton & Coutts, 2016). Previous studies in other sports, such as soccer (Castellano et al., 2011; Lago et al., 2010) and Australian rules football (Ryan et al., 2017), have also identified lower running intensities during away matches. This observed effect could be due to a number of factors such as the influence of the home crowd, home officiating bias, familiarity, territoriality or increased travel which have all been purported to influence the so-called "home advantage" (Cunniffe et al., 2015; Staufenbiel et al., 2015). The latter may not be as relevant for the ESL since the stadia are in close proximity. However, mechanisms could relate to reduced sleep, and possibly ineffective physiological and psychological restoration from training-induced stress as a result (Whitworth-Turner et al., 2019). Conversely, Delaney et al. (2016) attributed the lack of any observed effect to the sample analysed (i.e. interchange players only), and suggested a reduced overall playing time and recovery between interchange bouts may permit higher intensities to be achieved in spite of match location.

The effects of season phase were investigated by Delaney et al. (2016) who again found no significant effect on average speed as the season progressed, whereas Kempton & Coutts (2016) found a moderate increase in average speed and HSR speed. Lastly, Twist et al. (2014) included an ESL team and NRL team within their analyses and found a general trend for displacement variables to increase for ESL and decrease for NRL when later in the season. Some authors suggest an increase in match running as the season progresses may be attributable to a concomitant increase in fitness (Kempton & Coutts, 2016; Ryan et al., 2017). However, this remains speculative and reinforces the aforementioned need for a regular (proxy) measure of fitness to affirm this. In fact, the opposite may also be true for any given individual due to accumulated residual fatigue, or fitness may remain stable since the training priority during in-season for most team sports is generally maintenance of physical qualities (Dalton-Barron et al., 2018; McMaster et al., 2013). The latter may help to explain the lack of any significant effect of season phase found by Delaney et al. (2016). A potential mechanism for a decrease in metreage could include changes in ambient air temperature, since exercising in warm or hot conditions (>30°C) may lead to increased physiological strain resulting in reduced aerobic capacity and force production (Girard et al., 2011; Périard et al., 2015). Moreover, the most important matches are generally towards the end of the season, where teams compete in finals or attempt to attain as high ladder position as possible. Although, it is unclear whether match importance would have an influence on match running in rugby league, given that no effect was found in soccer (Bradley & Noakes, 2013).

The effects of a short match turnaround (<7 days) appeared to generally result in an increase in displacement variables for Murray et al. (2014) and Delaney et al. (2016), which is somewhat unexpected and difficult to explain. Conversely, Kempton & Coutts (2016) found shorter turnarounds to result in decreased average speed and HSR speed. Teams will typically prioritise recovery over training frequency during shorter match turnarounds since residual fatigue post-match may last up to 4 days (McLean et al., 2010; Moreira et al., 2015). However, the effectiveness of these recovery interventions and differing training loads could contribute to discrepancies found between studies (Delaney et al., 2016; Kempton & Coutts, 2016; Murray et al., 2014). Still, it has been suggested that players may be able to perform high intensity running bouts in the presence of neuromuscular fatigue (Roe et al., 2016). No reduction in displacement variables for shorter turnarounds may also be partially a result of squad rotations (Cunniffe et al., 2011), as such it has been suggested that individual match turnarounds should be included as an additional contextual factor to account for this (Dalton-Barron et al., 2018).

4.5. Influence of nutrition on match running

Using a block randomisation design, Bradley et al. (2016) investigated the influence of a high *vs* low carbohydrate diet in the lead up to a match, of which there were no substantial differences in match running demands or muscle glycogen availability between conditions. The lack of any increase in muscle glycogen availability may be due to the efficacy of the diet, individual differences (i.e. responders *vs* non-responders) or fidelity of the intervention (i.e. the extent to which the intervention was implemented as intended (Taylor et al., 2015). Irrespectively, the experimental design nor the univariate statistics employed would permit causal inference for any relationship found between glycogen availability and match running. However, such studies are still vital to understanding the appropriate dosage and feasibility of implementing a carbohydrate diet prior to the performance and should guide future research in the area. This is assuming a relationship exists between glycogen availability and increased capacity to sustain intermittent running, as has been consistently shown in previous experimental protocols (see Williams & Rollo (2015)). In other words, it may be possible to maximise the athlete's capacity to continuously work at a high intensity, even though the context of the match does not allow them to do so.

4.6. Influence of technical and tactical factors on match running

For technical and tactical variables, findings indicated movement increased whilst in defence (Gabbett et al., 2014), as well as the individual having the possession of the ball (Gabbett, 2012). Delaney et al. (2016) found an increase in movement when the tackle count was high, *vs*. Kempton & Coutts (2016) who found a decrease. This could somewhat be attributed to the inclusion of only interchange players for Delaney et al. (2016) and differences in positional responsibilities of middles to retreat and carry during defensive and attacking phases (Gabbett et al., 2008). Irrespective of the type of data (e.g. action frequencies, position, GPS displacement), all data collected during a match are signals, meaning they are sequentially dependent time-series. Any individual sampling point is dependent upon the previous point and will determine the position of the following point. This means that the order in which the data were collected (i.e. time) is an important dimension which is often discarded when data are discretised or reduced to action frequencies. By providing only the end discretised value for any given variable, it may be assumed that the data were organised in any number of ways, and as such do not capture the "ebs and flows" of the match. Whilst temporal data were collected, these studies only reduced sampling points of a single variable, effectively smoothing the data (Hulin et al., 2015), or summarising the total time (Delaney et al., 2016) within a particular activity (e.g. ball-in-play time). This still does not answer why movement occurs, only that it does in a particular order. To understand this, the data must be viewed with all relevant variables in a multidimensional space, which will be discussed further in the following sections.

4.7. Challenges with current approaches in data analysis

There are a number of key limitations in the current body of identified literature, a major one being the overreliance on statistics using only a single independent variable (i.e. contextual factor) to explain changes in match running, which is an inherently complex phenomenon. Five out of the 15 included studies utilised these statistics (Bradley et al., 2016; Gabbett et al., 2013, 2014; Gabbett, 2012, 2013), meaning discerning causation from purely associative relationships would be extremely difficult within their observational research designs (Stovitz et al., 2019). It is important that researchers and practitioners adopting a univariate approach seek to identify causal relationships so that appropriate actions are implemented (McCall et al., 2017; Nielsen et al., 2018). As well as reverse causality ($Y \rightarrow X$), an issue often observed in observational studies is the general lack of consideration of a common variable Z which influences X and Y ($X \leftarrow Z \rightarrow Y$, termed "confounder bias") (Pearl, 2000). When identifying influences or effects of independent variables on dependent variables, researchers will typically design experiments or quasi-experimental protocols to isolate the effect of a given treatment or factor. Conditions are then tightly controlled to increase confidence that this relationship is indeed causal. Match-demands related studies are observational by nature since it would be impossible to exactly replicate the conditions of any given match except the variable of interest. Including only a single contextual factor is analogous to an uncontrolled experiment whereby it is unclear whether the observed effect is due to the explanatory variable included or some other confounding factor. As such, as a minimum, researchers should include multiple independent variables within the same model and thereby control somewhat for confounders (Trewin et al., 2017; Weaving et al., 2017). This may be achieved through appropriate statistical analyses, such as ANCOVA or mixed effects models. These types of analyses also allow for dependency in datasets, a specific example being the dependency arising from repeated measures designs (Kenny & Judd, 1986), which were used by all 15 studies but were only accounted for in 5 (Delaney et al., 2016; Kempton & Coutts, 2016; Kempton et al., 2017; Quinn et al., 2015; Twist et al., 2014). Nonetheless, even these statistical methods still have limitations in that they are examples of univariate approaches, meaning they only include a single dependent variable in their analyses.

With the exception of Twist et al. (2014) who utilised a multivariate ANOVA, all other studies used univariate statistical analyses, albeit t-tests or general linear models. This points to a potential lack of consideration for the covariance (i.e. the between-variable information) within their respective datasets. Whilst univariate analyses have proven useful and have merit, such as more easily interpretable models, they inherently do not capture the complexity of match running. Since velocity and acceleration are both derivatives of distance and time, all measures will be strongly coupled and not independent of each other. It is therefore not surprising in this systematic review that distance, speed, or acceleration seem to concomitantly change in the same direction for a given contextual factor. For example, Gabbett (2013) found all three measures increased when the match was won, outlining a collinear effect. There may also be highly intercorrelated contextual factors used to explain changes in displacement, leading to redundancy and multicollinearity issues in datasets, which may in turn lead to instability in least squares regression-based models (Sinan & Alkan, 2015). In fact, the more features or variables included in the model, the more complex the dataset becomes meaning that researchers are often faced with higher dimensional data, inflating any chances of encountering highly correlated variables (Till et al., 2016). Variance inflation factors (VIFs) are a common diagnostic to detect the presence of multicollinearity, particularly when a VIF value >10 for any predictor variable. In a recent study by Weaving et al. (2019), there were VIF values seen in the thousands for various training load measures including displacement metrics, indicating a serious multicollinearity issue. To account for this, the authors used an orthogonal data analysis approach through partial least squares correlation analysis (PLSCA). Similarly to principal component analysis (PCA), this approach is underpinned by singular value decomposition (SVD), a dimension reduction technique that eliminates multicollinearity by creating a set of new composite variables that are completely independent from each other (Till et al., 2016). The composite variables themselves may then be used to project displacement in a reduced multivariate space. Alternatively, SVD could also be used as a variable selection tool to identify a subset of uncorrelated predictor variables that maximise the amount of information in the whole dataset, effectively removing any redundancy prior to any further data analysis (Peres & Fogliatto, 2018).

4.8. Considering rugby league competition from a systems thinking approach

This systematic review has identified various influences on match running within rugby league. However, the notion of an "influence" itself originates from a reductionist's approach, meaning that causality is monodirectional, i.e. for every cause, there is a preceding effect. With this comes a specific line of enquiry, whereby the overall objective of this approach is to break down complex phenomena into a set of easily defined linear relationships between static, isolated variables. This idea lends itself to the general linear model whereby all the independent or explanatory variables within the model explain changes in the dependent variable, and any unexplained variability is captured in the error term. Alternatively, it could be said that modelling individual match running is equivalent to modelling human movement behaviour (i.e. decision-making) – a phenomenon that emerges from the synergistic, non-linear interactions of many components. By extension, rugby league match-play can be thought of and analysed as a nested complex system, consisting of components operating at different levels (i.e. molecular, organismic, and social levels) and timescales (Balagué et al., 2017). Within each level there is self-organisation among the components in response to changes to the system or changes to the constraints that surround the system (McGarry et al., 2002). More generally, the concepts within the systems thinking approach have been previously applied to many different areas within sports science-related literature including movement systems (Davids et al., 2003), sports injuries (Hulme et al., 2019), and sports performance (Stöckl et al., 2017).

There are many different branches of systems thinking, and in particular there are many machine learning techniques which have may have considerable applicability in analysing complex systems. Indeed, artificial neural networks have been used extensively for explaining tactical decisions and team behavioural patterns in sport, particularly within soccer (Ramos et al., 2018) and basketball (Bourbousson et al., 2010a, 2010b). However, collective game behaviours are not independent of match running, since displacement occurs as a result of a tactical decision. Therefore, considering both constructs together may help us to understand "why" movement occurs. For example, a player makes a tactical decision to change their position based upon the information they can gather from the game state (Dutt-Mazumder et al., 2011). As such the ball location and the player's interpersonal distance in relation to both their teammates and the opposition will inherently be important factors to consider, and has been shown in other football codes (Ric et al., 2014). Furthermore, once the decision is made to run, there may be various individual constraints impacting upon the efficacy of the movement itself. These may include various physiological (e.g. strength, speed, and power) and anthropometrical (e.g. chronological age, body fat, lean body mass, and bone mineral content) qualities, which have successfully discriminated between positions (Comfort et al., 1998; Meir et al., 2001) and playing standards (Baker, 2001; Baker & Newton, 2008; Jones et al., 2016, Till et al., 2016, 2017) previously.

Even so, unexplained variability is inherent even in complex machine learning models due to a number of reasons, such as potentially immeasurable yet important latent constructs like motivation during the match (Gastin et al., 2013). Whilst pseudo measures of these constructs are sometimes available, such as the match attendance representing match importance, there are likely a number of variables that have not even been considered which are still important. This then means that all models, albeit statistical or machine learning, will suffer from availability of information bias to some extent, meaning we only input into the model whatever we can collect as opposed to what is important. A pertinent example of this bias within this systematic review is the lack of information from both competing teams in match-play, evidenced by the number of studies with single team samples (80%). This also reveals a further issue for practitioners whereby the generalisability of findings identified in these studies is unknown since the samples used are not random and the between-team variability in match running has not been quantified.

4.9. Limitations

Within this systematic review, the results were narratively reported and a meta-analysis was precluded due to the heterogeneity in the identified studies' methodologies, statistical analyses, and contexts. Whilst this study concerns the latter, a high degree of bias was anticipated due to studies only including a limited number of contextual factors. Therefore, the absence of a meta-analysis means there are a large breadth of results to interpret, which may lead to confusion. Some of the limitations of each identified study have been commented on throughout, and as such results should be taken with scepticism, and would likely better serve as a starting point for practitioners to analyse match running within their own contexts. Indeed, future work should seek to include more information about the contexts in which the match running data were collected, so that findings are more generalisable and meta-analysis may be possible. Moreover, whilst not the focus of this study, contact events were not considered which form a considerable contribution to the external biomechanical load imposed upon players during match-play (Vanrenterghem et al., 2017). Knowledge of how and why collisions vary in different contexts would be valuable information for practitioners to inform their training programmes.

5. Conclusions

This study has highlighted some of the potential contextual factors associated with match running in professional senior male rugby league. Factors related to the individual, match result and match conditions, the team and opposition strength, technical and tactical demands, as well as various spatial and temporal characteristics were all associated with changes in individual match running. Future work adopting a reductionist approach should look to understand causal mechanisms underpinning player and team movements through the inclusion of multiple contextual factors concurrently as a minimum, which specifically utilise unique spatial and temporal data including both teams during the competition if possible. However, practitioners and researchers should be mindful that match running is a complex phenomenon and should therefore strive to be more cognizant of the whole system instead of only a few isolated components. This could be achieved by embracing the complexity in match running through the use of a systems thinking framework, and analyses which account for this complexity.

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