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REVIEW

Unlocking the potential of big data to support tactical performance analysis in professional soccer: A systematic review

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Abstract
In professional soccer, increasing amounts of data are collected that harness great potential when it comes to analysing tactical behaviour. Unlocking this potential is difficult as big data challenges the data management and analytics methods commonly employed in sports. By joining forces with computer science, solutions to these challenges could be achieved, helping sports science to find new insights, as is happening in other scientific domains. We aim to bring multiple domains together in the context of analysing tactical behaviour in soccer using position tracking data. A systematic literature search for studies employing position tracking data to study tactical behaviour in soccer was conducted in seven electronic databases, resulting in 2338 identified studies and finally the inclusion of 73 papers. Each domain clearly contributes to the analysis of tactical behaviour, albeit in – sometimes radically – different ways. Accordingly, we present a multidisciplinary framework where each domain's contributions to feature construction, modelling and interpretation can be situated. We discuss a set of key challenges concerning the data analytics process, specifically feature construction, spatial and temporal aggregation. Moreover, we discuss how these challenges could be resolved through multidisciplinary collaboration, which is pivotal in unlocking the potential of position tracking data in sports analytics.

Keywords: *Football, big data, tactical analysis, team sport, performance analysis*

Highlights

- Over the recent years, there has been a considerable growth in studies on tactical behaviour using position tracking data, especially in the domains of sports science and computer science. Yet both domains have contributed distinctly different studies, with the first being more focused on developing theories and practical implications, and the latter more on developing techniques.
- Considerable opportunities exist for collaboration between sports science and computer science in the study of tactics in soccer, especially when using position tracking data.
- Collaborations between the domains of sports science and computer science benefit from a stronger dialogue yielding a cyclical collaboration.
- We have proposed a framework that could serve as the foundation for the combination of sports science and computer science expertise in tactical analysis in soccer.

1. Introduction

Increasingly large amounts of data are collected in professional soccer for the purpose of match analysis. Player positions are tracked continuously during practice and competition using state-of-the-art tracking systems (Rein & Memmert, 2016). Due to recent technological innovations, there has been a particular

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increase in systems and devices that collect and provide position tracking data. These innovations have been embraced and widely adopted by professional sports organizations, and the use of data is broadly considered as a potential game-changer in professional sports (Rein & Memmert, 2016). However, there is still a lot to be gained, as the availability of data has increased much more rapidly than the scientific advancements required to valorise data in the domain of soccer (Rein & Memmert, 2016).

One of the more interesting opportunities provided by the availability of position tracking data in soccer is the study and analysis of tactical behaviour. Tactical behaviour is an important determinant of performance in team sports like soccer, and refers to how a team manages its spatial positioning over time to achieve a shared goal (i.e. scoring), while interacting with the opponent under constraints of the conditions of play (Gréhaigne, Godbout, & Bouthier, 1999; Rein & Memmert, 2016). In the past, the analysis of tactical behaviour has mostly been based on manually annotated data and observation by experts (Rein & Memmert, 2016). As these assessments mainly describe what happens with the ball, they only provided insights into the "who and what", and – albeit with poor accuracy – the "where, and when" of on-ball behaviour (Vilar, Araujo, Davids, & Travassos, 2012). However, as tactical behaviour is the result of the interaction between all players on – and off the ball (Gréhaigne et al., 1999; Rein & Memmert, 2016), truly analysing the mechanisms behind it requires accurate data on all 22 players and the ball. Therefore, position tracking data provides the opportunity to accurately study the mechanisms behind tactical behaviour in soccer. However, despite its potential in the analysis of tactical behaviour, so far it has mainly been used to determine player activity profiles to monitor player loading and subsequently prescribe training loads (Sarmento et al., 2014).

The large amounts of position tracking data challenge the data management and analytics methods native to sports (Gandomi & Haider, 2015), and unlocking its potential in the study of tactical behaviour requires solving these challenges first (Rein & Memmert, 2016). Although data can be considered 'big' based on the three V's (volume, variety, and velocity Gandomi & Haider, 2015), there are no universal benchmarks for these dimensions. Whether a dataset is considered big or not heavily depends on the interplay between these dimensions, and is generally considered to be domain specific (Gandomi & Haider, 2015). One could consider data 'big' when it exceeds the 'three-V tipping point': the point where traditional data management and analysis methods become inadequate (Gandomi & Haider, 2015). The overall process of deriving information from position tracking data can be divided into two components: data management and data analytics (Gandomi & Haider, 2015; Labrinidis & Jagadish, 2012). These components can each be divided further into various sub processes, each associated with their own challenges (Gandomi & Haider, 2015; Labrinidis & Jagadish, 2012). Challenges to the data management component have been thoroughly addressed in previous reviews. Manafifard, Ebadi, and Moghaddam (2017) for example provide a detailed review on the strengths and weaknesses of optical tracking systems, and what could be done when it comes to (pre-)processing to improve data collection with these systems in the future (Manafifard et al., 2017). In other examples Stein et al. (2017) and Rein and Memmert (2016) (both specific to soccer) and Gandomi and Haider (2015) (in general) have addressed the various data streams that need to be brought together in the analysis, and how this poses a challenge to data management systems commonly employed in soccer (Gandomi & Haider, 2015; Rein & Memmert, 2016; Stein et al., 2017). Challenges to data analytics on the other hand, and specifically the challenge of aggregating raw position data into interpretable spatiotemporal features that capture the complex dynamics of tactical behaviour, have received considerably less attention so far.

Contributions from the domain of sports science and the domain of computer science are typically characterized by distinctly different research paradigms. Research from the domain of sports science on tactical behaviour is generally characterized by deductive reasoning in forming a hypothesis and designing an (experimental) study. Teams are for example considered as complex dynamical systems and hypotheses regarding their behaviour are formulated based on expectations rooted in such a theoretical perspective (Araújo et al., 2015; Balague, Torrents, Hristovski, Davids, & Araújo, 2013; Seifert, Araújo, Komar, & Davids, 2017) To study whether soccer teams behave like dynamical systems, and to study how manipulating constraints affects the system's behaviour, data is typically collected for a specific research purpose, *after* the research question has been formulated. In most sports science contributions, this means data is collected in an experimental setting – most frequently a set of manipulated small-sided games – which is designed based on the research question and related hypotheses. The raw position tracking data is then usually aggregated into features that operationalize the hypotheses and represent group level behaviour, such as team centroids or team surface areas (Frencken, Lemmink, Delleman, & Visscher, 2011;

Memmert, Lemmink, & Sampaio, 2017). A feature like the team centroid reduces the complex behaviour of a group of players into interpretable behaviour by aggregating their movements into a single feature, in the case of the centroid, representing the average positions at a point in time. These aggregated features are then used to study the interaction between groups over time. This can be insightful for the development of specific theories. However, by reducing the team's performance to these aggregated features, relevant aspects of the complexity of this behaviour may be overlooked. Aggregating the behaviour of 11 players into one feature, like the centroid, might for example, fail to capture the different movements of sub-units (i.e. defensive line) on the team and thereby fail to fully capture the complexity of tactical behaviour.

On the other hand, contributions from the domain of computer science, as well as the application of its techniques – also described as 'data science' – utilize a distinctly different research paradigm. Computer science concerns the theoretical foundations of (computationally retrieving) information, typically yielding advanced analyses and high-level representations of large and complex data (Gudmundsson & Horton, 2017). For example, Knowledge Discovery (also referred to as 'Data Mining') is all about identifying the robustness of patterns that are found without formulating hypotheses about the existence of these patterns. Although both sports- and computer science adopt a deductive approach, the type of empirical evidence for these deductions is radically different. In sports science, (experimental) research designs typically aim to confirm or reject a hypothesis that was formulated based on theory as discussed in the previous paragraph. In computer science, new modelling techniques are evaluated by testing the robustness of the generated model. This quantification of robustness can then be used to verify whether a discovered pattern was 'significant': How likely is it that this pattern was found by chance? In other words, whether the technique worked successfully is deduced based on the empirical evidence to quantify the robustness. Explorative techniques such as subgroup discovery (Grosskreutz & Rüping, 2009) have the benefit that patterns can be discovered based on how 'interesting' they are, for example based on how accurate the pattern is (ratio between true positives and false negatives) or how many instances it applies to. Typically, computer science techniques have been developed in the context of large datasets with many possible patterns to explore, as it is not always clear which patterns can be expected a-priori. From position tracking data, many features can be derived resulting in a multitude of features. Therefore, the data mining tools from computer science are well-suited to deal with the complexity of position tracking data.

One could argue that unlocking the full potential of big data for sports – science and practice – requires bringing the two domains, and thus two distinctly different paradigms, together, as their contributions can be regarded complimentary. Doing so however, requires one to understand the challenges and opportunities of a multidisciplinary interplay between the domains of sports- and computer- science (Rein & Memmert, 2016). Several authors have addressed this question in previously published narrative studies: Rein and Memmert (2016) have discussed the potential of applying big data in tactical analysis, but also discussed how it challenges the methodological approaches native to sports sciences. Memmert et al. (2017) have applied techniques from both domains to a position tracking dataset of one professional match to illustrate the potential of using contributions from both domains. Gudmundsson and Horton (2017) have provided an overview of – mostly – computer science techniques available in sports for the study of spatiotemporal behaviour. Stein et al. (2018) have described the entire process from data acquisition, to storage, to ultimately analysis and interpretation, in an attempt to provide an overview of different segments of the process of utilizing big data for performance analysis. Although these studies all refer to challenges as well as the potential of multidisciplinary collaboration, none of these studies actually put the contributions from both domains into one framework nor do they discuss the operationalization of such a collaboration.

The integration of fundamental computer science work into applied settings (i.e. data science) has been discussed in other applied domains, illustrating the benefits of integrating these techniques in different settings. Gandomi and Haider (2015) have discussed the challenges and opportunities of applying big data in general, while more specific examples of integrating computer science techniques in specific settings outside of sports include forecasting and pattern mining of financial time-series in economics (Cao & Tay, 2003), development of individual video recommendation systems in media and entertainment (Davidson, 2010), and spatiotemporal analysis of geographical data in geographic and earth sciences (Peuquet & Duan, 1995). These examples illustrate that application of techniques from computer science can support analysis and innovation in other areas. With the current review, we aim to outline a framework that integrates contributions from the domains of sports science and computer science in the study and analysis of tactical behaviour in soccer using position tracking data, and discuss the additional insights that can be gained from this integration. We specifically focus on the identification of challenges and opportunities with regard to the utilization of expertise from the domains of sports science and computer science, as both domains benefit from a conceptual model that outlines where each domain complements the other in analysing tactical behaviour in soccer using positional tracking data.

2. Methods

2.1. Literature search

A systematic review of the available literature was conducted according to PRISMA (Preferred Reporting Items for Systematic reviews and Meta-analyses) guidelines (Moher et al., 2015). A literature search was conducted on 14 June 2019 to identify studies that report the use of position tracking data to analyse tactical behaviour in soccer (Figure 2). Specifically, the following electronic databases were searched: Science Direct, Dimensions, Computer Science Bibliographies, PubMed, Scopus, ACM Digital Library, IEEE Xplore.

Titles and/or abstracts of all records in an electronic database were searched for the combination of the following search terms: soccer OR football AND tactic* OR strateg* OR formation* OR inter*player OR inter*team OR spatio*temporal NOT robo*.

Furthermore, additional studies to consider were identified by manually searching the reference lists of included papers.

2.2. Study selection

To be considered for this review, studies had to concern tactical behaviour and meet the inclusion criteria outlined in Table I. For the purpose of this review, tactical behaviour was defined as how a team or individual manages its spatial position over time to achieve a shared goal (i.e. scoring), while adapting to, and interacting with the opponent under constraints of the conditions of play (Gréhaigne et al., 1999). We operationalized this by searching for studies that at least included data and analysis on the interactions in space and time on the inter-team as well as intra-team level.

The first author conducted the first selection based on titles and abstracts conducted by the first author. Any study that clearly not met the inclusion criteria was excluded at this stage. When a confident decision based on the title and abstract could not be made, the study was included for full-text analysis. Next, the eligibility for inclusion was assessed based on analysis of full-text papers by the first author of this review. The final selection was then validated by at least one of the co-authors. Any ambiguities regarding the inclusion of papers of the review until consensus was reached.

2.3. Data extraction

All included studies were classified as sports science (1) or computer science (2) based on the journal or conference they were published in, as well as the associated keywords. Next, information on data collection was extracted. To review the contributions of all studies to the components of feature construction and modelling & analysis (Figure 1), we extracted data on the spatial aggregation features, window selection, and techniques applied for analysis. Furthermore, data was extracted on the link with match performance, the problem definition or aim of the study, and the inclusion of a theoretical definition of tactical behaviour to review the interpretability of all included studies. Finally, all findings were categorized and put into a single framework (Figure 2), that will serve as the context for the discussion of our findings, and as a proposed structure for the utilization of expertise from the domains of sports science and computer science in the study and analysis of tactical behaviour. All data extraction

Table I. In- and exclusion criteria for the systematic literature search.

Inclusion criteria	Exclusion criteria
• Published in the last 15 years	• No full-text available (in English)
• Full-text publication English	• Analysis based only on notational data
• Published as a peer-review journal or conference paper	• Data collected in futsal
• Tactical analysis based on position tracking data (LPM, GPS or Optical Tracking)	• Data available for only one team
• Data collected in matches or SSGs	• Data available of less than two players
• Data collected in soccer	

Notes: LPM, Local Position Measurement system with Radio Frequency Identification (RFID) (Frencken et al., 2010); GPS, Global Positioning System; SSGs, Small-sided games.

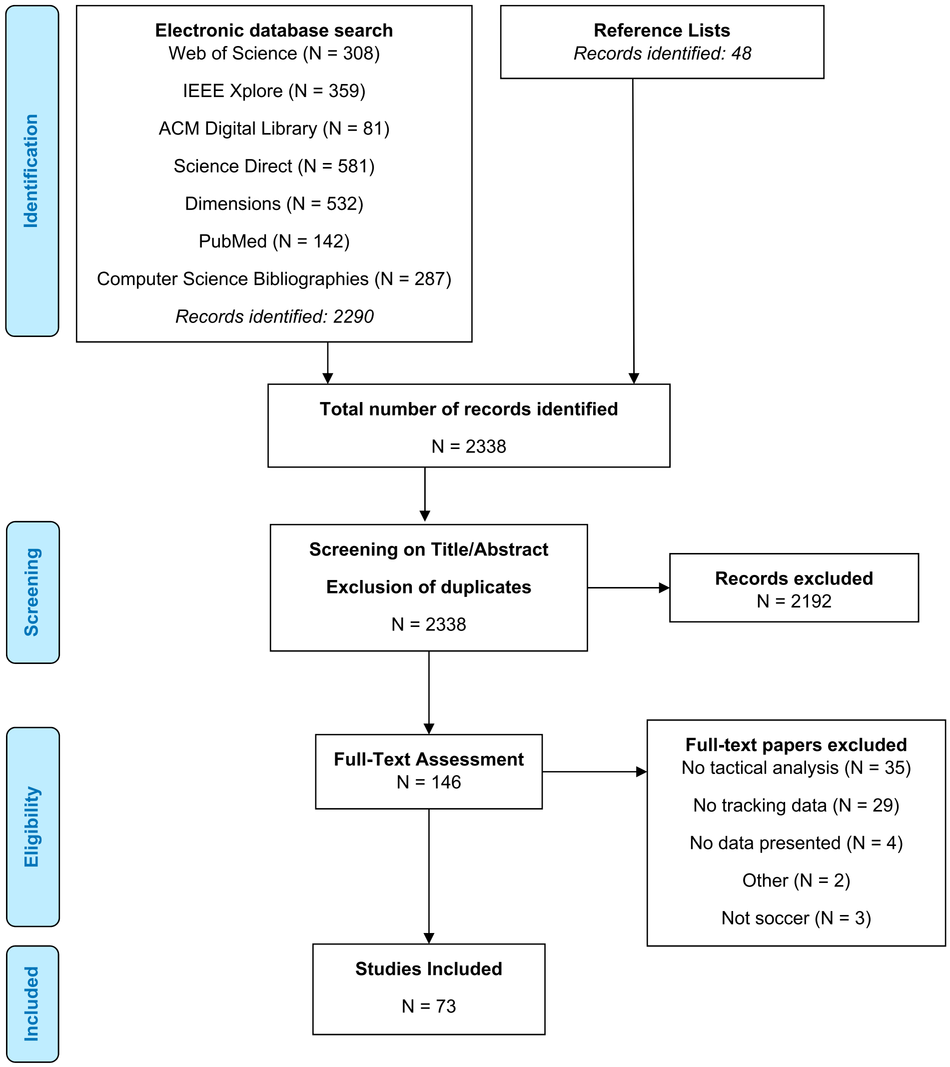

Figure 1. Flowchart of systematic literature search (conform PRISMA guidelines) where the number of included studies during each of the stages of the search process is shown. The main reasons for exclusion based on full-text assessment, as well as the number of included studies are shown at the bottom.

was based on full-text assessment by the first author of this review. Data extraction tables (Supplementary Data) were developed based on consensus between all authors.

3. Results

The initial database search returned 2290 records to be considered for inclusion. An additional 48 papers were identified based on manual inspection of the reference lists of already included papers (see 'Identification' in Figure 1). As a result, a total of 2338 records were screened based on title and abstract, of which 146 were considered for full-text assessment (see 'Screening' in Figure 1). After full-text assessment, 73 records were excluded because they did not meet our inclusion criteria (see 'Eligibility in Figure 1). The remaining 73 records (Aguiar, Gonçalves, Botelho, Lemmink, & Sampaio, 2015; Andrienko et al., 2017; Aquino et al., 2016a, 2016b; Baptista et al., 2018; Batista et al., 2019; Barnabé, Volossovitch, Duarte, Ferreira, & Davids, 2016; Bartlett, Button, Robins, Dutt-Mazumder, & Kennedy, 2012; Bialkowski et al., 2014a, 2014b, 2014c, 2016; Castellano, Fernandez, Echeazarra, Barreira, & Garganta, 2017; Chawla, Estephan, Gudmundsson, & Horton, 2017; Clemente, Couceiro, Martins, Mendes, & Figueiredo, 2013a, 2013b, 2014; Couceiro, Clemente, Martins, & Machado, 2014; Coutinho et al., 2017, 2018; Duarte et al., 2012, 2013a, 2013b; Fernandez & Bornn, 2018; Figueira, Gonçalves, Masiulis, & Sampaio, 2018; Filetti, Ruscello, D'Ottavio, & Fanelli, 2017; Folgado, Gonçalves, Abade, & Sampaio, 2014a; Frencken et al., 2011; Frencken, De Poel, Visscher, & Lemmink,

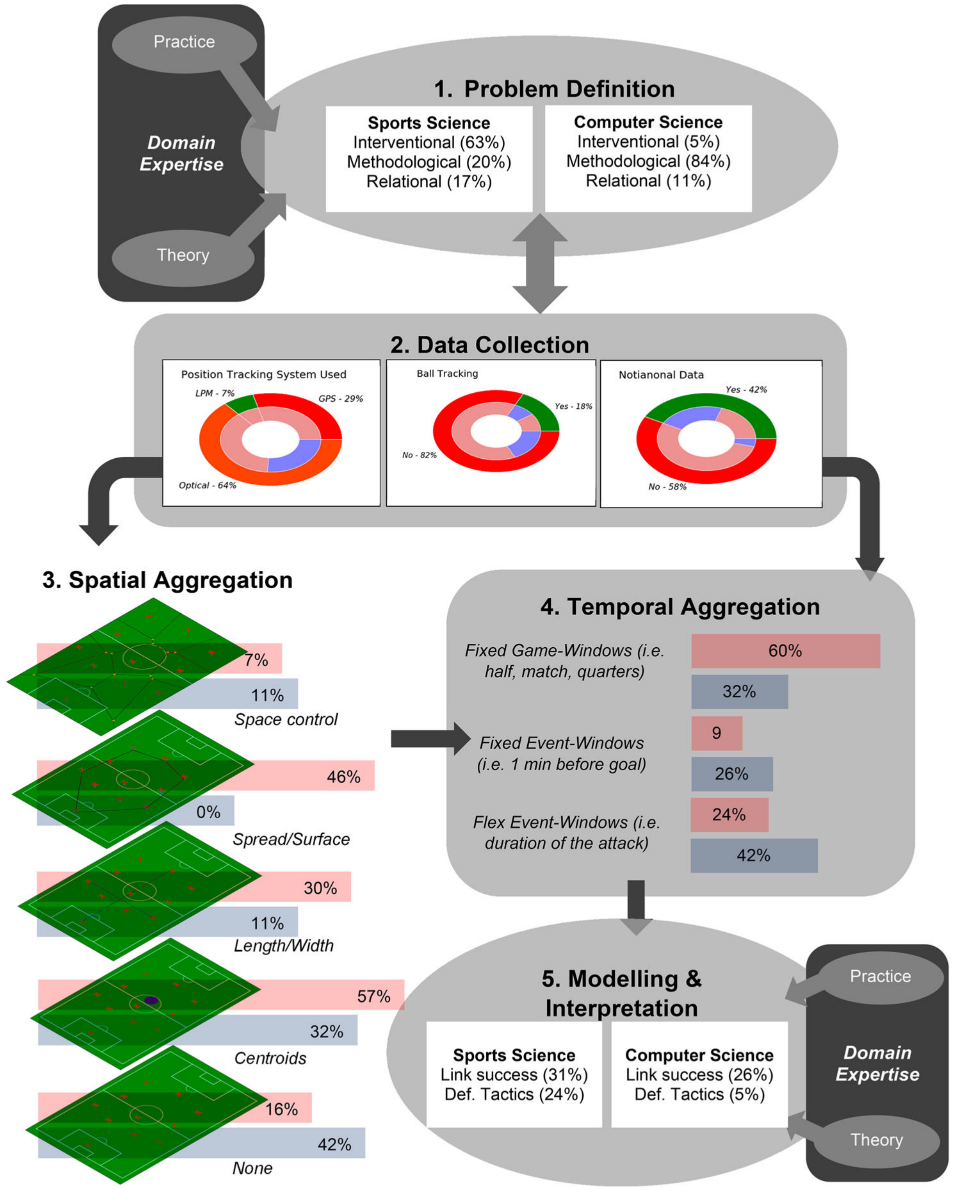

Figure 2. Conceptual framework for the combination of sports science (translucent red bars) and computer science (translucent blue bars) expertise in the study of tactical behaviour in soccer. Based on the results from the current systematic review. Bars with percentage represent the relative occurrence of a certain method or feature within a domain. Abbreviations: SSG, Small-Sided Games; LPM, Local Position Measurement.

2012; Frencken, van der Plaats, Visscher, & Lemmink, 2013; Frias & Duarte, 2014; Gonçalves, Figueira, Maçãs, & Sampaio, 2014; Gonçalves et al., 2017a, 2017b; Gonçalves, Marcelino, Torres-Ronda, Torrents, & Sampaio, 2016; Grunz, Memmert, & Perl, 2012; Gudmundsson & Wolle, 2010; Janetzko et al., 2014; Janetzko, Stein, Sacha, & Schreck, 2016; Knauf, Memmert, & Brefeld, 2016; Link, Lang, & Seidenschwarz, 2016; Machado et al., 2017; Memmert et al., 2017; Memmert, Raabe, Schwab, & Rein, 2019; Moura, Barreto Martins, Anido, De Barros, & Cunha, 2012; Moura et al., 2013, 2016; Olthof, Frencken, & Lemmink, 2015, 2018, 2019; Power, Ruiz, Wei, & Lucey, 2017; Ramos, Lopes, Marques, & Araújo, 2017; Rein, Raabe, & Memmert, 2017; Ric et al., 2017; Sampaio, Lago, Gonçalves, Macas, & Leite, 2014; Sampaio & Macas, 2012; Siegle & Lames, 2013; Silva et al., 2014a, 2014b, 2015, 2016a, 2016b; Spearman, Basye, Dick, Hotovy, & Pop, 2017; Stein et al., 2015, 2016; Travassos, Gonçalves, Marcelino, Monteiro, & Sampaio, 2014; Vilar, Araujo, Davids, & Bar-Yam, 2013, 2014a, 2014b; Wei, Sha, Lucey, Morgan, & Sridharan, 2013; Yue, Broich, Seifriz, & Mester, 2008a, 2008b; Zhang, Beernaerts, Zhang, & de Weghe, 2016) were included for analysis in the review. Of the included papers, 54 (74%) were qualified as sports science papers and 19 (26%) as computer science papers.

Below, we will describe the results of our systematic analysis of the literature. We examine various categories, including: Problem Definition, Data Collection, Spatial Aggregation, Temporal Aggregation, and Modelling & Interpretation. We analyse the included studies numerically, by describing how often various categories occur. Moreover, we summarize the different categories in a visual framework where we combine the expertise from sports- and computer-science domains (see Figure 2). This figure will be used as a guide to explain the body of literature that encompasses the study of tactical behaviour. Full details and data extracted from the included studies can be found in the supplementary data.

3.1. Problem definition

In most included sports science studies, research questions were driven by theoretical or practical domain expertise from for example, physiology, behavioural science or psychology. Studies frequently aimed for practical implications, and study designs and data collection result from the research question. When looking at the problem definitions and aims of the included sports science papers, 63% studied the effect of an intervention on tactical behaviour, as is illustrated by the work of Olthof et al. (2018, 2019), who studied the effect of manipulating pitch sizes on tactical behaviour in different age groups, and the work of Gonçalves et al. (2016, 2017a, 2017b), who studied the effect of numerical imbalance between teams on tactical behaviour (Gonçalves et al., 2017a, 2017b; Ric et al., 2017). Twenty percent studied a variable/method to quantify tactical behaviour, as is illustrated by the work of (Link et al., 2016), who conceptualized a new feature called “dangerousity” to quantify offensive impact. Finally, 17% studied the relationship between variables (see ‘Problem Definition’ in Figure 2), as for example illustrated in the work of Rein et al. (2017) who studied the relation between pass effectiveness quantified by the change in space control and number of outplayed defenders and success in 103 Bundesliga games (Rein et al., 2017).

In most included computer science studies on the other hand, research questions were driven by theoretical and methodological domain expertise from for example computer sciences, mathematics or data science. These studies frequently aimed for new methodological approaches and techniques rather than practical implications. Furthermore, in many cases the design could be considered data-driven: rather than formulating hypotheses based on theory and collecting data in an experimental set-up to test these hypotheses, studies used large sets of available data and generated hypotheses from the data. When looking at the problem definitions of these studies, 5% studied the effect of an intervention or constraint, as there is the work by Bialkowski et al. (2014a, 2014b, 2014c), studying the impact of home-advantage on the dynamic formation of a team on the pitch. The majority (84%) of computer science contributions however, studied a new technique or model (mostly classification or clustering problems), like the work by Fernandez and Bornn (2018), who proposed an improved model for measuring space control, the work by Andrienko et al. (2017), proposing a new feature to quantify pressure on a player, or the work by Bialkowski et al. (2014a, 2014b, 2014c) and the work by Grunz et al. (2012) proposing new methods to identify patterns and formation in the data (Bialkowski et al., 2014a, 2014b, 2014c; Grunz et al., 2012). Finally, 11% studied prediction or probability problems, as illustrated in the work by Spearman et al. (2017), or Chawla et al. (2017), who proposed models to predict if a pass would arrive at a team-mate or not (Chawla et al., 2017; Spearman et al., 2017) (see ‘Problem Definition’ in Figure 2).

3.2. Data collection

The type, quality, and quantity of data strongly influences the research questions that can be answered within the study of tactical behaviour, as well as the approach that can be used (see ‘Data Collection’ in Figure 2). Most studies (64%) used optical tracking data as this is the system of choice in many professional competitions. As opposed to LPM and GPS systems, optical tracking systems typically allow tracking of the ball. However, they are also known to have a lower accuracy in comparison to wearable tracking devices, especially LPM (Frencken, Lemmink, & Delleman, 2010). Work by Mara, Morgan, Pumpa, and Thompson (2017) revealed optical tracking systems suffer measurement errors in the range of −2.5 m–2.5 m in measuring covered distance on 20–100 m (change of direction) runs (Mara et al., 2017). Although these errors could limit the use of optical tracking data for the analysis of physical performance, the subsequent errors of 0–0.5 m in measuring position still allow for accurate assessment of tactical behaviour, as the error margin is small enough for data to still represent actual positions. Only a minority (18%) of the studies used ball tracking, and a much larger part of the studies (42%) used the more time-consuming notational event data to study ball events. Sensor systems (36%) and experimental designs (48%) like small-sided games (SSGs) were exclusively used in sports science studies. As sensor systems do not allow ball tracking, event-based analyses are impossible without notational event data (Figure 2).

3.3. *Spatial aggregation*

Tracking the X and Y position of 22 players and the ball 1–100 times a second results in sizeable amounts of data, even for one match, as well as a high complexity as the 22 degrees of freedom of the system allow for numerous potential interactions. Therefore, most studies aggregate raw position data by reducing the spatial positions of all players into spatial features. More specifically, spatial aggregation refers to the process of constructing features that capture group-level behaviour per timeframe and allow one to derive contextual meaning, as these features reduce the system's complexity to an interpretable level (see 'Spatial Aggregation' in Figure 2). These features can be constructed at the macro level (full team), as for example in work by Frencken et al. (2012), who aggregated the positions of the team into one team cerntroid, at the micro-level (subgroups of at least two players), like in the work by Memmert et al. (2017), who aggregated the positions of a subgroup (e.g. defensive line) into a line centroid, or even at the level of the individual, as in the work by Olthof et al. (2015), who measured the average distance of all players to the team centroid (e.g. stretch index). Furthermore, combinations of spatial aggregates can be used to construct composite measures of spatial (sub-)group interactions, as for example presented in the work by Goes, Kempe, Meerhoff, & Lemmink, 2019, who constructed a measure of pass effectiveness by using line centroids, team spread and team surface areas. Most sports science studies (84%) used some form of spatial aggregation, most frequently (57%) centroid related features (Frencken et al., 2011; Yue et al., 2008a, 2008b), followed by team surface areas and spread (Moura et al., 2012) (46%), length and width (Folgado, Lemmink, Frencken, & Sampaio, 2014b) (30%), and space control (Rein et al., 2017) (7%). Distribution amongst computer science studies is somewhat similar, with 58% of the studies using spatial aggregates, specifically centroid features (32%), length and width (11%) and space control (11%).

However, as data mining techniques can directly be applied to the positional data without aggregating it into features, a small minority of the sports science studies (16%), and nearly half of the computer science studies (42%) do not use spatial aggregation. In these cases, patterns in the raw data can, for example, be detected using unsupervised machine learning techniques like clustering, as is illustrated by the work of Grunz et al. (2012), Knauf et al. (2016), and Machado et al. (2017), who all mine patterns in the data by clustering the raw positions in some way (Grunz et al., 2012; Knauf et al., 2016; Machado et al., 2017). Furthermore, machine learning techniques also allow for the inclusion of many features and studying their non-linear relationships, like there is the work by Power et al. (2017), and Spearman et al. (2017), who model pass risk and reward and the probability of a pass arriving and include a multitude of features (Power et al., 2017; Spearman et al. 2017). In many of these computer science contributions, the algorithm does feature selection automatically. The main benefit of this is that instead of creating features based on a-priori assumed relationships between entities, (hidden) relationships can be uncovered from the data. As features are not created and selected based on expectations of the user, but rather based on their importance in the algorithm, they could prove to be a better depiction of patterns in the data.

3.4. *Temporal aggregation*

To extract information, statistically compare, or model time-series of either raw data or aggregated spatial features, data needs to be aggregated within the temporal domain as well (see 'Temporal Aggregation' in Figure 2). Temporal aggregation refers to the summation of data over a given time-window, by for example computing the mean value of a given feature. We consider three different methods for temporal aggregation: first of all, data can be aggregated (e.g. averaged) over time windows with a fixed size, independent of the context of the game (Sampaio & Macas, 2012). In such methodologies, for example, data is aggregated over the course of a half or full match, or another time window with a fixed duration. Secondly, data can also be aggregated over a window with a fixed size that is linked to match events. An example is looking at the 3 s following a pass (Goes et al., 2019), or the 30 s before a goal (Frencken et al., 2012). Finally, data can be aggregated over windows with a flexible size. In these cases, windows are always linked to events with variable durations like a sequence of passes or running trajectories (Rein et al., 2017; Spearman et al. 2017). The majority of sports science studies (60%) utilized fixed windows in which they often aggregate spatial data over the course of a full SSG or match, while only a minority aggregates over fixed (9%) or flexible

(24%) event-based windows. However, the majority of computer science studies aggregated over fixed (26%) or flexible (42%) event-based windows, and only a minority (32%) aggregated over fixed windows independent of context.

3.5. *Modelling & interpretation*

Most included sports science studies utilized statistical models, and models rooted in the dynamical systems theory like relative-phase (Palut & Zanone, 2005) and entropy (Pincus, 1991, 1995) analyses that allow for time-series analysis. These models are generally based on linear relationships and allow comparison of multiple conditions, the study of relationships between variables, and testing specific hypotheses. Furthermore, they are interpretable on the level of individual features. Most computer science studies on the other hand used methods that are in comparison computationally complex (i.e. require more computations and therefore more processing power), like various machine learning approaches. These approaches allow the study of (non-) linear complex relationships amongst many different features and the discovery of hidden patterns in the data, but require specific (programming) skills and often high-performance computing clusters, and can be harder to interpret, especially without the methodological domain expertise.

To be able to interpret the practical impact of a study on behaviour, it needs to be clear what (tactical) behaviour was actually studied, and how changing this behaviour impacts performance (see 'Modelling & Interpretation' in Figure 2). Only 19% explicitly defined tactical behaviour, of which only one study Janetzko et al. (2014) was classified as a computer science study. Analysing the extracted definitions, three common elements were identified: Tactical performance/behaviour refers to (1) the dynamic positioning and organisation in space and time, of a team and its players on the pitch, in interaction with and adapting to the movement of the ball, (2) movement of the opponents, and conditions of play, (3) and constitutes more than just the sum of individual parts. As according to these criteria tactical behaviour is emergent, it cannot be studied by breaking down the behaviour of a team into 11 individual parts and analysing them separately, as behaviour is the result of interaction. Furthermore, only 30% used match performance indicators (e.g. outcome, shots on goal) in their study of tactical behaviour. Most (86%) investigated the link between tactical features and match performance using performance indicators related to shots or goals. Interestingly, there is little consensus on the relation of most tactical features with performance (outcome). On the one hand, studies that investigated the link between often-used tactical features like the team-centroid did not find a clear relationship with offensive events and performance (Bartlett et al., 2012; Frencken et al., 2012). On the other hand, authors who used more complex tactical features like the team surface area or spread (Moura et al., 2012, 2016), or composite features related to passing (Rein et al., 2017; Spearman et al. 2017) did report some relationship with performance. These rather inconsistent reports on the effect of tactical features on performance, as well as the large variety of possible tactical features to analyse, highlight how difficult it is to uncover and interpret consistent and generalizable patterns in tactics.

4. Discussion

With this review, we aimed to put the contributions of sports and computer science to the analysis of tactical behaviour in soccer using position tracking data into perspective. Both domains contributed significantly to the study of tactical behaviour, and provide a set of unique approaches towards analytics. Our results show that there are considerable differences in methodology. We propose that both domains benefit from a cyclical collaboration and embedding each other's domain expertise. Therefore, we provide a framework for optimizing this collaboration by linking the contributions from both domains to different parts of the analytical process that entails the analysis of tactical behaviour using position tracking data (Figure 2). Our framework could support the field of sports analytics and specifically the analysis of tactical behaviour, and result in a better translation to practice.

We have argued in our introduction that research from sports science and research from computer science is characterized by distinctly different, and to some extent contrasting research paradigms. Our results have revealed that this was also true for research specifically concerning the study of tactical behaviour using position tracking data. The sports science studies we have included in this review were predominantly characterized by deductive reasoning in which hypotheses were formed based on theory, and tested in mostly experimental settings. This is clearly illustrated by many of the included sports science works, like those by Aguiar et al. (2015), Baptista et al. (2018), Coutinho et al. (2017, 2018), Duarte et al. (2012), Frencken et al. (2011, 2013), or Olthof et al. (2015, 2018), who all presented a theoretical framework to study and understand tactical behaviour that is rooted in the dynamical systems theory (Aguiar et al., 2015; Baptista et al., 2018, 2019; Coutinho et al., 2017, 2018; Duarte et al., 2012; Frencken et al., 2012, 2013; Olthof et al., 2015, 2018), and specifically designed experimental set-ups with small-sided games to analyse behaviour against the backdrop of this framework. The aims of these sports science studies are generally focused on advancing our understanding of tactical behaviour, and applying the findings in practice to for example improve training design or talent identification and development. This is illustrated in studies like those by Gonçalves et al. (2016, 2017a, 2017b), who studied the impact of numerical imbalance and spatial constraints on tactical behaviour in small-sided games, to optimize training design (Gonçalves et al., 2016, 2017a, 2017b). Or the work by Olthof et al. (2015, 2018, 2019), who studied the impact of field size on tactical behaviour in small-sided games and compared that behaviour to behaviour seen in a real match, to find out what design would be the best format to improve match performance.

The included computer science studies on the other hand, provide a very different perspective. The studies we included from this domain generally do not present any theoretical context to explain tactical behaviour, nor do they contain hypotheses about what this behaviour would look like or how teams or players would react to certain manipulations or stimuli. We would like to argue that based on our findings, this is not necessarily a shortcoming but rather a matter of a different aim and perspective. Rather than aiming for an increased understanding and practical implications in sport, the computer science studies we included were typically focussed on advancing methodology and computational techniques for data processing, modelling and extraction of information by means of inductive designs that centre on data mining, feature extraction and visual analysis. This is illustrated by for example the work of Bialkowski et al. (2014a, 2014b, 2014c, 2016), and Wei et al. (2013), who presented new methods to detect formations and identify positional roles based on data based on large observational dataset collected in competition. Or the work of Stein et al. (2015, 2016), and Janetzko et al. (2014, 2016), who presented a data visualization and exploration techniques that aim to optimize the workflow of video-analysts in professional soccer organizations (Janetzko et al., 2014, 2016; Stein et al., 2015, 2016). Or the work of Chawla et al. (2017), who presented a model to accurately classify successful and non-successful passes based on data. None of these works extensively discus practical applications, explain the findings based on a theoretical understanding of tactical behaviour or advance our understanding of behaviour, have experimental designs or result in direct practical implications on the level of training and performance. However, this is by design, as these contributions all aimed to propose new techniques, features and data processing and visualization routines instead.

The distinct difference in contributions from both domains to the research on tactical behaviour is also confirmed by other recent review studies on similar topics. In systematic reviews characteristic for sports science like those by Sarmento et al. (2014) and Ometto et al. (2018), the focus is on how position tracking data can be used to analyse performance and monitor loading, or how to manipulate small-sided games to change behaviour. On the other hand, in typical computer science survey papers like the one by Perin et al. (2018), Gudmundsson and Horton (2017) and Stein et al. (2017), the focus is more technical, discussing topics from data management to visualization and how to develop analytical tools. Given the fundamental differences in expertise and methodology, collaboration between both domains can therefore be regarded a key challenge.

Most studies included in this review fit well into one end of the sports science – computer science spectrum, and collaborations between domains are still relatively sparse. However, we have also included multiple studies that gravitate towards the middle of the spectrum and illustrate the added benefit of a synergy between both domains. The studies by Link et al. (2016), Rein et al. (2017), and Goes et al. (2019), are examples of sports science work that utilizes observational designs in which large datasets were collected in competition and used for the development and validation of new features that assess some aspect of performance (Goes et al., 2019; Link et al., 2016; Rein et al., 2017). Although in these studies most involved scientists had a background in sports science, at least some of them also had a background computer science helping them applying computer science techniques for data processing, visualization and analytics coming from domains like mathematics, data mining and machine learning, and information processing. Despite their methodology, these studies were still classified as sports science as their aim was not necessarily the sole development of a new approach or technique, but rather the validation of these approaches by studying their relation to successful performance and applying the approach for the purpose of performance analysis. The work by Goes et al. (2019) for example resulted in a new metric to quantify the effectiveness of a pass that was constructed using clustering techniques and then applied for player evaluation purposes, while the work by Rein et al. (2017), was focussed on applying multiple metrics that assess pass effectiveness by studying their relation to offensive performance.

As we identified several sports science studies that utilized techniques from other domains to advance their research, we also identified multiple computer science studies that did the same. The studies by Power et al. (2017), Spearman et al. (2017), Andrienko et al. (2017) and Fernandez and Bornn (2018) can all be regarded as examples of studies that predominantly involved expertise from computer and data science, but who also involved domain expertise from sports (science) (Andrienko et al., 2017; Fernandez and Bornn, 2018; Power et al., 2017; Spearman et al. 2017). These studies focussed on feature development and modelling, as they constructed models for the assessment of pass risk and reward, pressure, space control and pass probability. Different to the sports science examples mentioned before, the scope of these studies was methodological, yet they typically validated their approach and its assumed relation to performance based on domain expertise, and provided several examples of practical use cases based on data collected in competition. These examples from sports science and computer science studies that utilize expertise from other domains illustrate the additional benefits that can be gained and can in some ways be regarded as templates for future collaborations.

The included studies are illustrative of collaborations between the domains of computer science and sports science suggest contributions from both domains are compliant rather than concomitant. We therefore propose that collaboration between sports science and computer science in the process of studying tactical behaviour using position tracking data should be a cyclical rather than a parallel one. Sports science tests theory and translates practical problems into research questions. By applying techniques from computer science to sports science research designs one could come to different answers to research questions. These answers might differ in the sense that sports scientists could assess different aspects of performance, but they could also differ in the sense that these methods allow for a more in-depth answer. The other way around research questions deduced from theory and observation by sports science, can be used by computer science to define the scope of their search for, and development of appropriate technologies to derive information from position tracking data. Computer science provides the tools to gain in-depth knowledge and enables sports science to test increasingly complex hypotheses and ask new questions. As both domains bring relevant expertise in relation to conducting and interpreting tactical analyses, we propose that impactful analytics relies on the combination of expertise from both domains.

The quality (i.e. accuracy, sampling frequency, inclusion of ball data) and quantity of available data have a big impact on most types of research and cannot be ignored in any discussion of sports analytics. Due to technological advancements, lowers costs, and growing interest (Rein & Memmert, 2016), we have seen an increase in the availability and quality of data in soccer, similar to big data developments in other areas, providing numerous opportunities (Gandomi & Haider, 2015), like opponent-analysis, scouting and performance optimization on a team and individual level. However, based on our results, these opportunities only seem to be seized to a limited extent. Most sports science studies are characterized by experimental set-ups in which small samples of data are collected in a specific population, to answer a predetermined research question (Olthof et al., 2015; Travassos et al., 2014). Although this kind of research has allowed us to draw general inferences about what drives tactical behaviour of groups, the small sample sizes and highly specific circumstances that are often different from a real match also limit the use of findings from these studies in real-life tactical analysis. As tactical behaviour is highly dependent on the context (Gréhaigne et al., 1999; Rein & Memmert, 2016), larger real-life datasets collected in actual competitive matches in combination with methodology that enables capturing complex patterns might allow one to draw conclusions about performance with a stronger ecological validity. Of course, causation and correlation should not be confused, but with large enough datasets, the discovered patterns carry some weight and at the very least provide a good basis for developing new theories that can be further examined in more controlled settings. On the other hand, handling and analysing much larger datasets challenges back-end processes (i.e. storing, pre-processing and querying) and analytics (i.e. aggregation and feature construction) that are not typically addressed by sports science research, and can thus be regarded a key challenge. The domain of computer science typically focuses on technological developments within these processes, and collaboration could advance the ability of sports science to work with increasingly large datasets.

As illustrated by the results in this review, the majority of sports science studies utilizes low-level (simple to compute and high reduction of complexity) spatial features like the team centroid (Folgado et al., 2014; Yue et al., 2008a, 2008b), that aim to capture group-level behaviour in one feature. The computation of these features is relatively easy, and their computational cost is low, yet as illustrated by the results, they have limited value. Features like the team centroid have often been developed to study tactics in small-sided games, but seem incapable of fully capturing the complex dynamics of an 11-a-side match (Goes et al., 2019). Combining computer science expertise on for example data mining and machine learning, with sports science theory provides many opportunities to innovate in this aspect. A potential example could be applying the work of Bialkowski et al. (2014a, 2014b, 2014c, 2016), that has resulted in methodology to automatically and dynamically identify formations and positional roles. Applying this method in sports science research like that of Memmert et al. (2017), Goes et al. (2019) or Siegle and Lames (2013), who all use line centroids in which the lines are based on manual annotation of fixed positional roles, could lead to different answers and new insights. The other way around, applying the theoretical framework of dynamical systems theory that is presented in for example the sports science work by Frencken et al. (2012, 2013), to feature construction in computer science work like that on quantifying pressure by Andrienko et al. (2017), could lead to advanced methods that use coupling between features and movement synchrony of players to quantify pressure, defensive strategies and off-ball performance of offensive players. These are typical examples of cyclical collaboration. The outcome of a collaboration like this would for example allow one to innovate the way we analyse the performance of a team during the game, to support decision-making by the coach in near-time, to analyse the opponent before the match by studying patterns that characterise their successful attacks, or to identify specific patterns to emphasize and train in the own team.

Ultimately, spatial features – no matter their complexity – hold little meaning when aggregated over a full match, and temporal aggregation is essential to place spatial behaviour in a temporal context (Gréhaigne et al., 1999; Rein & Memmert, 2016). Most included sports science studies aggregated over fixed windows independent of game-context, like a match or half (Duarte et al., 2013a, 2013b; Gonçalves et al., 2017a, 2017b), which limits interpretability. We argue that deriving meaning from spatial features requires the use of event-based time-windows, which is more common in computer science studies (Andrienko et al., 2017; Chawla et al., 2017; Fernandez and Bornn, 2018), as using event-based time-windows allows one to draw conclusions about for example a pass, dribble or set-piece. On such a small timescale, it is much easier to find structural patterns than on the level of the entire game. This in turn would allow one to answer questions like what defines an effective attack, or successful dribble. Although this might seem like another opportunity for sports science to implement existing computer science expertise, this one is less straightforward than spatial aggregation, and adequate temporal aggregation can be regarded as a key challenge. As time-series analysis is typically challenging for most machine learning techniques (Fu, 2011), and sport and behavioural sciences actually have a lot of expertise in time-series analysis, one could argue innovation here would definitively be on the brink of interaction between both domains.

Despite the often underlined potential (Memmert et al., 2017; Rein & Memmert, 2016; Stein et al., 2017) of position tracking data to study tactical behaviour, in sports, and specifically in soccer, the application is still relatively limited (Rein & Memmert, 2016; Folgado et al., 2014). Our results demonstrated the contributions to this topic have increased substantially over the recent years, and already resulted in an in-depth understanding of tactics in soccer. However, so far, these studies have had little practical impact, and the potential of position tracking data does not seem to be fully utilized so far. We argue that changing this requires domain expertise from sports science as well as computer science embedded within a multidisciplinary approach, which is a key challenge for sports analytics. It also requires a clear link between methodology, findings and real-life performance (i.e. answering the question "how does this help me/is this related to winning the game?" asked by "practioners"). Understanding behaviour therefore requires an approach that at least evaluates a certain aspect within the context of others, as well as answers the key performance question "how does (changing) this behaviour impact our performance".

With this systematic review, we provided an evaluation of contributions from sports science and computer science to the study of position tracking data for the purpose of tactical analysis in soccer, and we have shown how an interplay between both domains could results in innovative contributions to the field of sports analytics. One major limitation of the current review is its narrow scope, as we largely ignored essential components of the data analytics process like data acquisition, storage, management, visualization, as well as ethics and privacy issues (Perin et al., 2018; Stein et al., 2017). However, doing so allowed us to discuss the opportunities for position tracking data to impact tactical behaviour, whereas previous reports have merely touched upon its potential. This has resulted in the discussion of a set of challenges concerning the data analytics process, specifically feature construction, spatial and temporal aggregation that could be resolved by multidisciplinary collaboration, which is pivotal in unlocking the potential of position tracking data in sports analytics.

5. Conclusion

With this review, we have shown the considerable opportunities for collaboration between sports science and computer science to study tactics in soccer, particularly when using position tracking data. Our systematic review highlights that sports- and computer science research on tactical behaviour contains distinctly different contributions. We proposed a framework that could serve as the foundation for the combination of sports science and computer science expertise in tactical analysis. It has become clear that the collaborations between both domains benefit from a stronger dialogue yielding a cyclical collaboration: sports science identifies problems and tests theory hypotheses, computer science develops robust techniques to solve such problems, and sports science in turn adjusts theories and derives practical implications from data by implementing them.

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