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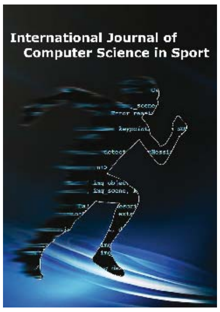

A development framework for decision support systems in high-performance sport

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Abstract

Decision making in sport involves forecasting and selecting choices from different options of action, care, or management. These processes are conditioned by the available information (sometimes limited, fallible, or excessive), the cognitive limitations of the decision-maker (heuristics and biases), the finite amount of available time to make the decision, and the levels of risk and reward. Decision support systems have become increasingly common in sporting contexts such as scheduling optimization, skills evaluation and classification, decision-making assessment, talent identification and team selection, or injury risk assessment. However no specific, formalised framework exists to help guide either the development or evaluation of these systems. Drawing on a variety of literature, this paper proposes a decision support system development framework for specific use in high-performance sport. It proposes three separate criteria for this purpose: 1) Context Satisfaction, 2) Output Quality, and 3) Process Efficiency. Underpinning these criteria there are six specific components: Feasibility, Delivered knowledge, Decisional guidance, Data quality, System error, and System complexity. The proposed framework offers a systematic approach for users to ensure that each of the six components are considered and optimised before, during, and after developing the system. A DSS development framework for high-performance sport should help to improve both short and long term decision-making in a variety of sporting contexts.

KEYWORDS: DECISION-MAKING, MANAGEMENT, INFORMATION, SPORT, OPTIMIZATION.

Introduction

In sporting settings, players, coaches, physiotherapists, doctors, and general managers continually face decisions relating to action, care, or management in various contexts. For example, in a match a player has to choose between shooting, passing, or dribbling; in a timeout a coach has to draw a play to be executed on the next ball possession; a doctor has to decide if a player can keep playing or if they require substitution; a general manager has to choose a draftee on draft night or who to hire as a new head coach (Grehaigne, Godbout, & Bouthier, 1997; MacMahon & McPherson, 2009; Morgulev & Galily, 2018) (Table 1). All of these decisions can be defined, among other factors, by the available information and time to make the decision, as well as the decision-making process utilised (Makridakis et al., 2019; Olade, 2004) (Figure 1).

Table 1: Example of different areas a professional sporting organization influences the operations side of the business.

BUSINESS OPERATION AREAS (SPORTS)			
STRATEGY	**RECRUITMENT**	**DEVELOPMENT**	**HEALTH CARE**
Game Style	Head coach	Athletic Performance	Medical
Roster Management	Young Players (Talent ID)	Skill Acquisition	Nutritional
Supporting Staff	Professional Players	Mental Performance	Psychological
Facilities			

As in many environments, problems faced by sporting organisations are context-dependent and sometimes complex, containing many interrelated parts and varying sources of information. Some of this information is precise, objective, and measurable, whereas others are uncertain, subjective, and/or immeasurable. In this context we define complexity as the condition of a system or situation that is integrated with some degree of order, but has too many elements and relationships to understand via simple analytical or logical means (Bennet & Bennet, 2004). Uncertainty, on the other hand, refers to a state of limited knowledge where it is not possible to precisely describe the existing reality, or predict future outcome(s) (Plous, 1993; Simon, 1978; Tversky & Kahneman, 1974). Risk is a specific state of uncertainty where some probable outcomes have an undesired effect or significant loss or harm (see also ‘prospect theory’ (D Kahneman & Tversky, 1979)). Improvements to technologies over the last 30 years have exponentially increased this complexity, largely through increased availability of data (Torres-Ronda & Schelling, 2017).

Difficulties associated with processing and understanding complexity as well as uncertainty in sporting decision-making problems can be explained using the theory of *bounded rationality.* This theory posits that the rationality of individuals is limited by the information they have available, their cognitive limitations, and the finite amount of time they have to make a decision (Simon, 1978). Usually, a limited, and sometimes *fallible*, amount of information is selected to reach an *heuristics*-based sufficiently satisfactory decision, a process known as *satisficing* (Simon, 1956). Further, the processing of information and decision making may be influenced by a number of *cognitive biases*, of which the decision maker may be unaware and may sometimes lead to perceptual distortion or inaccurate judgment (Tversky & Kahneman, 1974). Nevertheless, this does not necessarily imply that intuitive decisions are suboptimal. Depending on the complexity of the task and/or the time required to make the decision, fast-intuitive decisions are sometimes the only feasible option (D. Kahneman & Klein, 2009).

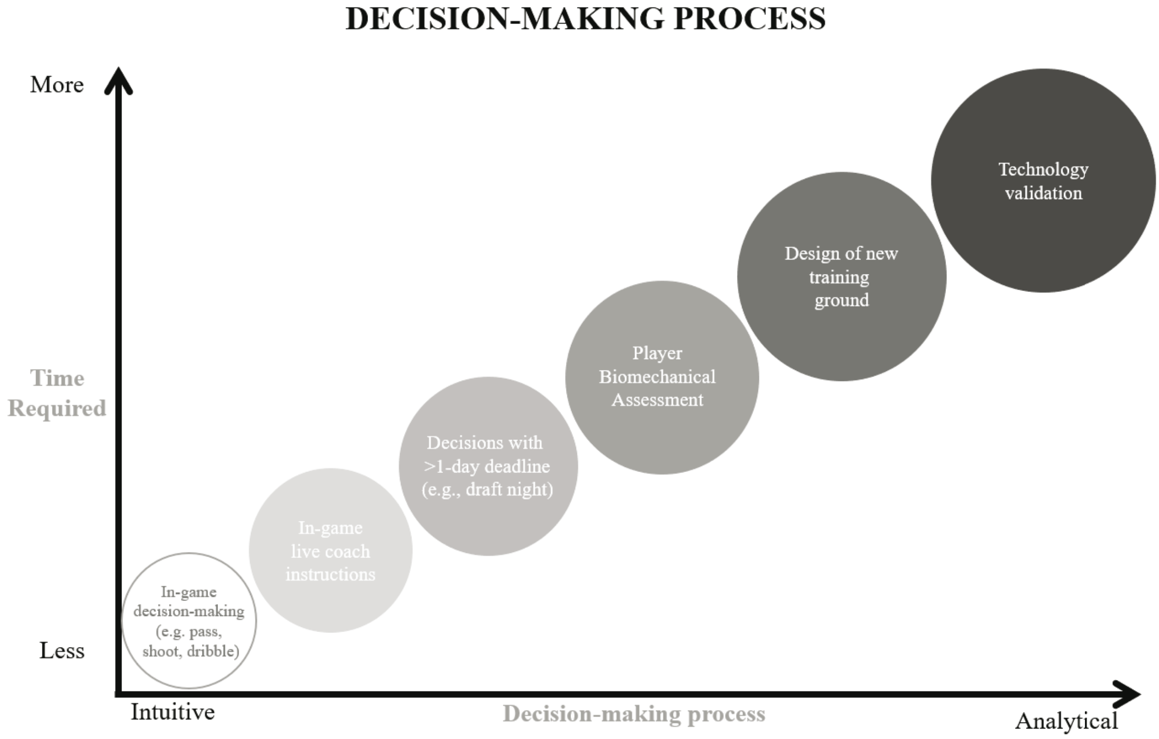

Figure 1: Examples of different decision-making situations considering four factors: the required/afforded decision-making time (vertical axis), the predominant cognitive mode (horizontal axis), task structure (bigger bubble = more structured), and the according suitability of DSS implementation (darker grey = more suitable). Personal adaptation of Hamm's Cognitive continuum (1988) from Olade (2009) for a sporting context.

An increased understanding of decision-making processes and common sources of error in different contexts can inform the development of information systems or when standardizing structured methodologies. Benefits include the minimisation of avoidable mistakes and increasing the proportion of enhanced decisions. In most complex problems it is difficult to trace cause-and-effect paths between variables because 1) many variables exist and 2) they exhibit considerable non-linearity in their relationships. Under these situations, complex problems should be understood by holistic thinking, fully engaged analytical processes, experience, and intuition to solve them (Bennet & Bennet, 2008). All of these features have the potential to be systematised through decision support systems.

This paper proposes a decision support system development (DSS) framework for specific use in high-performance sport. Below a rationale is provided for decision support systems to assist with informing the types of decisions mentioned above. Following this, several components of a good system are discussed and a DSS evaluation tool is proposed.

Decision support systems in Sporting Organizations

Decision support systems are computer-based information systems that provide objective evidence relating to the decision-making of organizations (S. Robertson, Bartlett, & Gastin, 2016; Sprague, 1980). They utilise historical data to generate a recommendation or assessment to a user, with the decision often provided based on output generated by a software-based algorithm or model (Kawamoto, Houlihan, Balas, & Lobach, 2005). DSS are designed to assist decision makers in environments in which the data available to aid decision making are voluminous and beyond human information processing capabilities, the link between decisions and outcomes is probabilistic or uncertain, or the decisions are repetitive (Kayande, De Bruyn, Lilien, Rangaswamy, & van Bruggen, 2009). In such environments it is unlikely that decision makers can consistently outperform recommendations from even a simple model-based DSS (Hoch & Schkade, 1996). Hence, there are number of reasons why a DSS should be implemented within an organisation (see (Bate, Hutchinson, Underhill, & Maskrey, 2012; Croskerry, 2005, 2009; S. Robertson et al., 2016)):

- the existing practice is largely subjective and/or solely expertise-based;
- the task has high value and impact in the organisation and thus warrants optimisation;
- there are multiple potential solutions and the organization desires identification of the most appropriate;
- there is current disagreement on how to approach the problem, or the optimal solutions are unknown;
- growth of good quality data allows for a re-structure of the decision-making process;
- the feasibility-to-impact ratio of the approached problem makes the investment on a new decision-making process worthwhile;
- the decisions are repetitive, and the process can be automated.

In sport, DSS have been used for purposes such as scheduling optimization (S. Robertson & Joyce, 2018; S. J. Robertson & Joyce, 2015), sport-modality classification (Hogarth, Payton, Van de Vliet, Connick, & Burkett, 2018), skill/movement evaluation and classification (Clermont, Osis, Phinyomark, & Ferber, 2017; Kovalchik & Reid, 2018; Novatchkov & Baca, 2013; Pernek, Kurillo, Stiglic, & Bajcsy, 2015; Richter, King, Falvey, & Franklyn-Miller, 2018; Rindal, Seeberg, Tjonnas, Haugnes, & Sandbakk, 2017; Whiteside, Cant, Connolly, & Reid, 2017; Whiteside & Reid, 2017; Woods, Veale, Fransen, Robertson, & Collier, 2018; Wundersitz et al., 2015), assessing decision-making and motor control (Maselli et al., 2017), talent identification and team selection (M. Lai, Meo, Schifanella, & Sulis, 2018; B Ofoghi, Zeleznikow, Macmahon, & Dwyer, 2013; Taha, Musa, Abdul Majeed, Alim, & Abdullah, 2018; Woods et al., 2018; Xie, Xu, Nie, & Nie, 2017), biomechanical analysis (Bertani, Cappello, Benedetti, Simoncini, & Catani, 1999; Ertelt, Solomonovs, & Gronwald, 2018; Kianifar, Lee, Raina, & Kulic, 2016; Kipp, Giordanelli, & Geiser, 2018; Richter et al., 2018), assessing injury risk (Carey et al., 2018; Li, Huang, Wang, Yu, & Ao, 2016; Lopez-Valenciano et al., 2018; Rossi et al., 2018; Ruddy et al., 2018; Thornton, Delaney, Duthie, & Dascombe, 2017), evaluating athlete/team performance (Blythe & Kiraly, 2016; Calder & Durbach, 2015; Dutt-Mazumder, Button, Robins, & Bartlett, 2011; Leicht, Gomez, & Woods, 2017; Link & Hoernig, 2017; Maier, Meister, Trosch, & Wehrlin, 2018; Montoliu, Martin-Felez, Torres-Sospedra, & Martinez-Uso, 2015; B. Ofoghi, Zeleznikow, Macmahon, Rehula, & Dwyer, 2016; Rein & Memmert, 2016; Sampaio et al., 2015), predicting athletes' response to training or competition (Abut & Akay, 2015; Bartlett, O'Connor, Pitchford, Torres-Ronda, & Robertson, 2017; Jaspers et al., 2018; Nagata et al., 2016), or assessing fatigue (Janssen et al., 2011; Ruddy et al., 2018; Zhang, Lockhart, & Soangra, 2014).

Once a specific decision-making process or problem has been selected as a candidate for DSS consideration, a number of challenges are required to be overcome in order for it to provide ongoing value to the organization (Hunt, Haynes, Hanna, & Smith, 1998). These challenges can be understood by the 3-gap framework proposed by Kayande et al. (2009) (Figure 2), which considers the relationships between the DSS model itself, the decision-maker's mental model, and the 'true' model (whilst acknowledging that the true model may either not be known or in fact ever attainable). To provide high-quality decision support, the gap between the DSS model and the 'true' model (Gap 2) must be small, whereas the gap between the user mental model and the DSS model (Gap 1) will influence the way the DSS is accepted and eventually implemented (Kayande et al., 2009).

To assess the quality of a service, Donabedian's framework (Donabedian, 1980) identifies three dimensions: 1) Structure, which describes the context in which the service is provided; 2) Process, which denotes the interaction between the service and the user; and 3) Outcome, which refers to the effect of the service on the user or organization (Donabedian, 1988). These dimensions should not be mistaken for attributes of quality, but rather they are the classifications for the types of information that can be obtained in order to infer whether the quality of the services is poor, fair, or good (Donabedian, 1988). Donabedian's framework has been the foundation of other evaluation frameworks specifically designed for information systems (Adelman, 1992; Khazanchi, 1991; Rhee & Rao, 2008), where the proposed dimensions are: 1) technical (model's logic, algorithms performance, and data flow); 2) empirical (the effect of the DSS on the decision-making process); and 3) subjective (how effectively and efficiently the users in a specific context interact with the DSS).

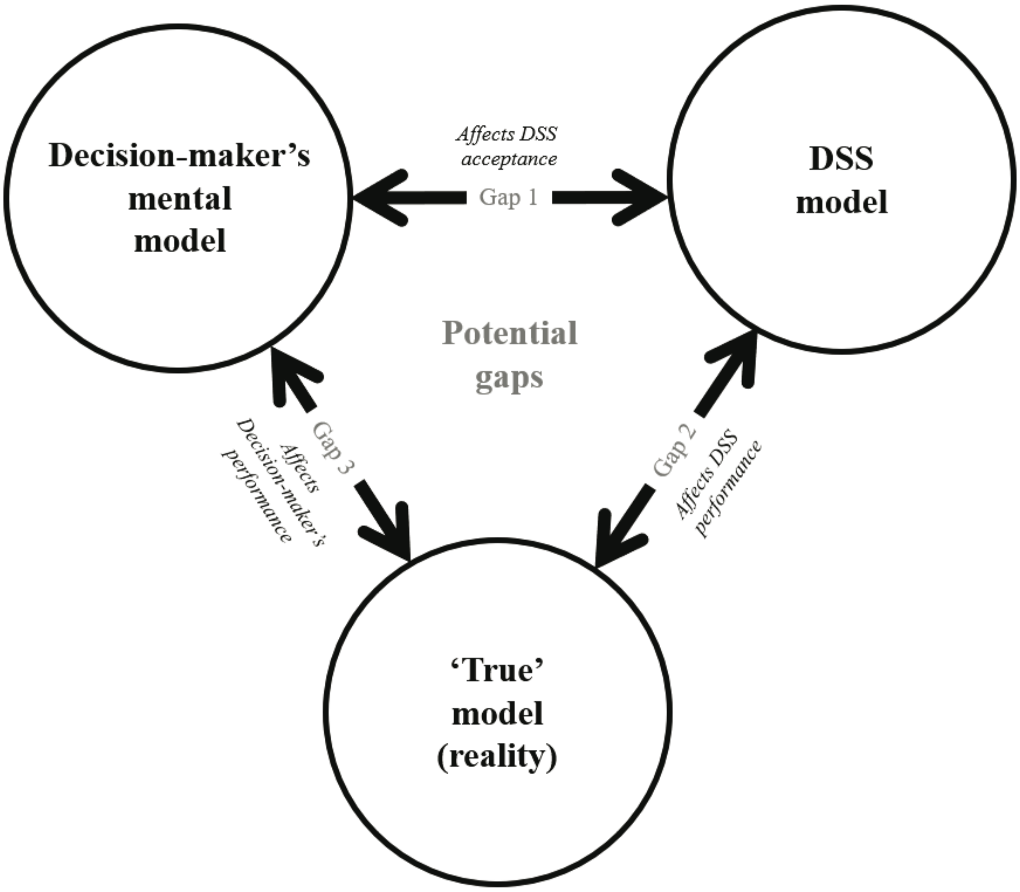

Figure 2: Kayande et al. (2009)'s 3-gap framework. The effect of gaps between Decision-maker's model, DSS model, and the True model.

A decision support development framework for high-performance sport

The Introduction detailed the importance of both DSS' performance and acceptance in an organisation (Kayande et al., 2009), along with a general model of DSS evaluation (Donabedian, 1980; Rhee & Rao, 2008). Drawing on this information, the remainder of this article proposes a DSS Development Framework for specific use in high performance sport.

Hence the proposed Framework consists of three overarching evaluation criteria: 1) Context Satisfaction, 2) Output Quality, and 3) Process Efficiency. These three criteria can be specifically assessed through six separate components: Feasibility, Delivered knowledge, Decisional guidance, Data quality, System error, and System complexity (Figure 3).

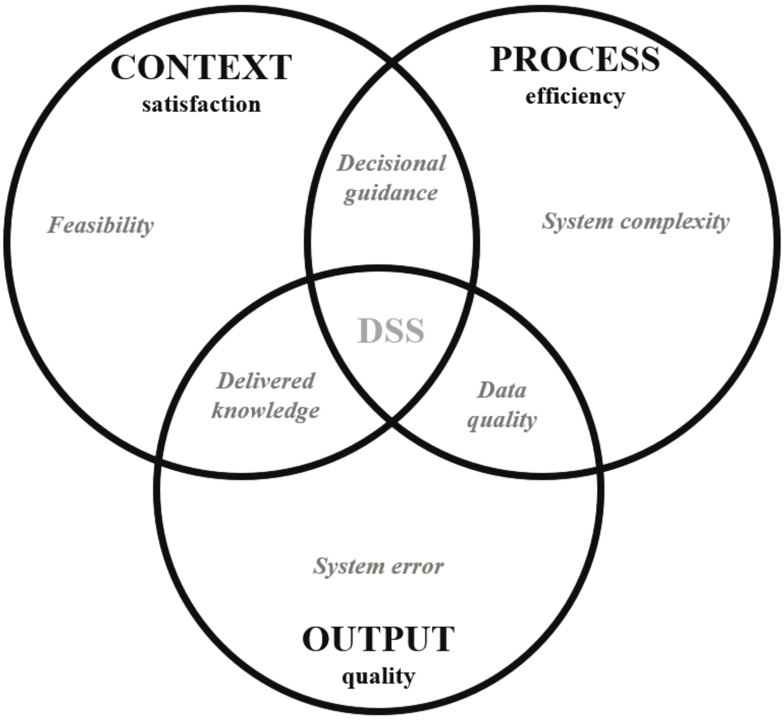

Figure 3: Measurement variables for the development and evaluation of a DSS.

Below, working definitions and examples for each of the three DSS criteria and their six accompanying components are provided for specific application in sporting contexts.

A. Context Satisfaction

The following components focus on the research required before starting DSS development, including an understanding of the specific organizational needs and resources, and expected delivered information (relevance and means).

1. Feasibility

Feasibility analysis provides a structured way of exploring the factors and risks affecting the potential for successful development and implementation of a DSS (Rhee & Rao, 2008). Feasibility can be addressed by examining the organizational context and the system's requirements, as well as by analysing the technical, operational, and economic circumstances (Rhee & Rao, 2008). Thus, successful implementation of a DSS can be interpreted as a function of its perceived costs (operational and economical) and its benefits (Mawhinney & Lederer, 1990). These can be summarized based on four aspects (Hogue & Hugh, 1984; Sprague, 1980):

1.1 *Organizational.* The developer of a DSS should consider the organizational context (previous practices and decision-making processes) in order to understand to what extent the organization is ready for a new implementation. The degree to which the proposed DSS fits with existing culture and organizational goals is also important. In some instances, the developer may also need to identify which changes would be required within an organization to facilitate DSS implementation. For example, the feasibility of a DSS for the purpose of informing selection of players in a draft may be increased if it can be shown that it would systematically improve the chances of selecting 'unexpected' top performers (such as: Tom Brady NFL draft pick #199, Albert Pujols MLB draft pick #402, Pavel Datsyuk NHL draft pick #171, Manu Ginobili NBA draft pick #57). The extent to which the DSS is viable within current practices of the organisation can be considered as its level of 'operational compatibility'.

1.2 *Technical.* Assessing the DSS technical requirements from an information-systems perspective (hardware and software), and from a process-efficiency point of view (time and resources required to gather the data, and analytical processing time), are critical to identify if the system will efficiently and satisfactorily resolve the targeted tasks. In this sense, one of the biggest technical challenges refers to how data are stored and shared across departments within the same organization, or when necessary, across different organizations or platforms. This is a key consideration in sport whereby front offices may be separated both structurally and even geographically from performance or training departments. To optimize this process, having a comprehensive data workflow is paramount. Although multiple options exist, a commonly used example is the Cross Industry Standards Process for Data Mining (CRISP-DM). As a methodology, CRISP-DM includes descriptions of the usual phases in a project, the tasks involved with each phase, and an explanation of the relationships between these tasks. As a process model, it provides an overview of the data mining life cycle. The life cycle model consists of six phases with arrows indicating the most important and frequent dependencies between phases. The sequence of the phases is not strict. In fact, most projects move back and forth between phases as necessary (Figure 4) (IBM, 2012).

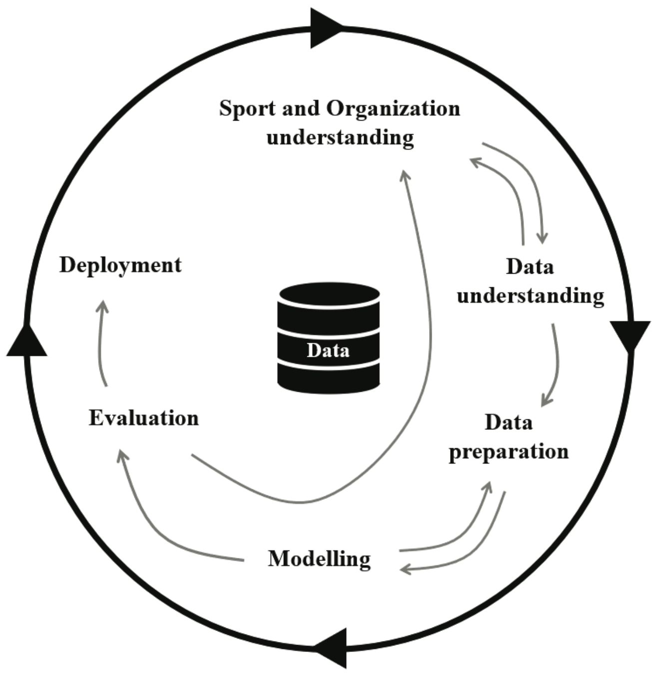

Figure 4: Cross Industry Standards Process for Data Mining (CRISP-DM) (Wirth and Hipp (2000) in Kelleher et al. (2015)).

1.3 *Financial.* Relates to the projected costs of implementing the proposed DSS, and whether those costs justify the potential benefits.

1.4 *Legal.* The developer must ensure that the data security measures, the individual's privacy rights, as well as the processes to access the system are legally compliant. For example, when using medical records, or any personal health information, in the USA the system requires compliance with the Health Insurance Portability and Accountability Act.

2. *Delivered knowledge*

From the data gathering to the specific decision-making action, different levels, or states, of acquired knowledge exist (Wali Van Lohuizen, 1986). These are from bottom-to-top: 1) data, 2) information, 3) structured information, 4) insight, 5) judgment, and 6) decision (Figure 5). Different operational processes must be undertaken to progress from one state to another. For instance, by selecting from data one obtains the next higher knowledge state, information (Holsapple, 2008).

Considering this granularity is fundamental for two reasons. First, it differentiates the usability of the delivered or available knowledge (lower levels have marginal use, whereas higher levels have more immediate use); and second, it helps to locate where the DSS sits in the decision-making process, considering the different steps before being able to make the final decision. Some DSS might be suitable solely for one of the intermediate steps. For instance, the system may target data selection or data analysis, depending on the purpose of the DSS and whether the system is meant for a final decision-maker or an intermediate.

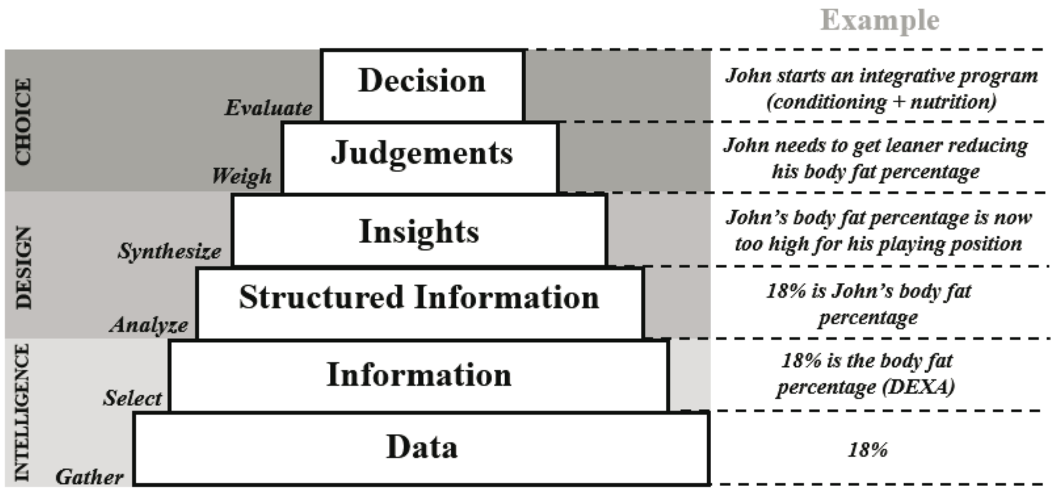

Figure 5: Knowledge as a progression of states. Based on van Louhizen (1986) and adapted from Holsapple (2008).

3. *Decisional guidance.*

Decisional guidance refers to the manner in which a DSS leads users to structure and execute their decision-making process (M. S. Silver, 1991). Morana et al. (2014) summarize the characteristics of Decisional guidance (Morana, Schacht, Scherp, & Maedche, 2014) based on the DSS': target (M. Silver, 2006), directivity (M. Silver, 2006), mode (M. S. Silver, 1991), invocation (M. Silver, 2006), timing (M. Silver, 2006), format (Gregor & Benbasat, 1999), intention (Gönül, Önkal, & Lawrence, 2006), and audience (Gregor & Benbasat, 1999) (Table 2). Appropriate Decisional guidance reduces the system restrictiveness (i.e., increases flexibility) while minimizing users' confusion (Montazemi, Wang, Khalid Nainara, & Barta, 1996) and helping to align the decision-maker's mental model to the DSS model (Figure 2) (M. S. Silver, 1991).

The decision-maker's mental model will be limited by cognitive biases, such as the human tendency to search for, interpret, favour, and recall information in a way that confirms one's pre-existing beliefs or hypotheses, also known as confirmation bias (Plous, 1993). Therefore, if the end-user does not understand the rationale behind the DSS recommendation, they may be sceptical of the output produced and therefore reluctant to use such a system (Kayande et al., 2009; Sanders & Manrodt, 2003). Moreover, DSS can be designed based on a priori knowledge or theories related to the question to solve (the so-called theory-driven or white-box models), based entirely on the available data and derivative statistical information (known as data-driven or black-box models), or based on a hybrid approach, combining theories and data (grey-box models) (Valatavičius & Gudas, 2017). The system's acceptance and its outcome interpretability will be related to the selected model design (Ribeiro, Singh, & Guestrin, 2016). The limitations of using solely theory- or data-driven models is a current topic of controversy and it has been discussed elsewhere (Hooshyar, Yousefi, & Lim, 2017). To overcome initial user scepticism and maximize acceptance, Kayande et al. (2009) recommend to incorporate in the DSS feedback that improves the interpretability of the process and helps the decision-maker to understand the relationship between their decision and the DSS recommendation (Chenoweth, L. Dowling, & St Louis, 2004; Kayande et al., 2009). This type of feedback serves as an assessment tool of the expert's bias. Examples could include; a physiotherapist who rates the movement efficiency of shorter players better than taller ones, a scout favouring predefined, static key performance indicators when performing talent identification, or a head coach who always criticises the same player's performance or explains a poor team performance from a reductionist point of view. Consequently, developers need to design a DSS that can provide an understanding of the discrepancy between the DSS recommendation and the expert's opinion (identification of expert bias). An explanation of why the DSS recommendation is better than the expert's is also required, in order to avoid potential user rejection of the system (Gönül et al., 2006; Kayande et al., 2009; F. Lai, Macmillan, Daudelin, & Kent, 2006; Limayem & DeSanctis, 2000; Montgomery, 2005).

System restrictiveness, the opposite of system flexibility (M. S. Silver, 2008), is defined as the way in which a DSS limits its users' decision-making processes (M. S. Silver, 1991). A very restrictive system supports only a small subset of all possible decision-making processes (Parikh, Fazlollahi, & Verma, 2001). System restrictiveness has implications for various substantive design decisions, including which functional capabilities to include in a DSS, which options to provide with each of those capabilities, and how to package the capabilities into a system (M. S. Silver, 2008). Some sources of restrictiveness are: constraints on functional capabilities (information-processing), data sets, models, parameters (input variables and options), or visual representations (M. S. Silver, 2008).

The desired Decisional guidance and restrictiveness of the DSS requires consideration when choosing the analytical processes and techniques embedded in the system. The DSS should aim for the most efficient and effective analytical process to solve a task while it meets the interpretability and the operational functions expected by the end-user. Many data mining techniques, using statistical or machine learning models, have been extensively employed as mathematical means of extracting and simplifying information from complex real-world tasks to support decision-making processes (Elragal & Klischewski, 2017; Safdar, Zafar, Zafar, & Khan, 2017). The complexity, interpretability, and accuracy, of these techniques may vary depending on the type of algorithm (Ribeiro et al., 2016). Different models can be used to solve the same problem, and with the same inputs, depending on the desired Decisional guidance and restrictiveness the developer wants for the DSS. For instance, different families of algorithms, such as regression, classification, rule-based, or clustering, each possess different operational characteristics (Witten, Frank, & Hall, 2011). Selection of one family of algorithm over another may also change the way in which the problem is framed for the end user. Nevertheless, in some instances the way in which a problem is framed cannot be altered, under these circumstances the decision should be objectively informed at least partially based on metrics included in Section B2 below.

Table 2: Considerations on Decisional guidance. Adapted from Morana, et al. (2014)

DECISIONAL GUIDANCE CONSIDERATIONS			
TARGET	**INTENTION**	**TIMING**	**MODE**
"What distinct aspect of decision making does the guidance influence? Selection, discovery, ranking, location…?"	"What is the overall goal of the DSS? To generate new knowledge ('one-time research'), to provide a faster recommendation.	"When does the DSS provide the recommendation? Real-time, retrospectively, prospectively?"	"How does the guidance mechanism work? Is it interactive or pre-defined?"
AUDIENCE	**DIRECTIVITY**	**INVOCATION**	**FORMAT**
"Is the end-user expert or novice on the topic and/or using DSS?"	"How explicit is the guidance from the DSS? Does it just inform or it suggests a solution?"	"How does the guidance process start? Automatically or on-demand?"	"Which is the channel to communicate the recommendation? Text, tables, graphs, image/video, audio…?

B. Output Quality

The following components review the factors related to the outcome produced by the DSS. These include the quality of the data inputted in the system, the system's degree of error, as well as the delivered knowledge (see Section A.2).

1. Data quality

Decision support systems rely on data to generate their outputs. Data quality problems are widespread in practice and reliance on data of poor or uncertain quality leads to less-effective decision-making processes (Chengular-Smith, Ballou, & Pazer, 1999; Fisher, Chengalur-Smith, & Ballou, 2003; Price & Shanks, 2008; Redman, 1997). To be able to assess 'quality' in practice, which is an abstraction or construct, requires its operationalisation into a measurable variable. Although multiple options exist, dimensions related to Data quality from InfoQ (Kenett & Shmueli, 2016) and InfoQual (Price & Shanks, 2005, 2008) (Table 3), which are the result of reviewing different approaches of information quality assessment, may be appropriate.

1.1 Meaning: refers to the selection of variables to collect, the temporal relationship between them, and their meaning in the specific context. Consideration of whether the purpose of the DSS is retrospective or prospective is required, hence if it aims to describe, to explain causality, or to forecast or simulate future events (Kenett & Shmueli, 2016). In explanatory models, where variables are operationalized constructs, variable selection is based on the role of the construct in the theoretical causal structure and on the operationalization itself. In predictive models, the focus is typically on association rather than causation, and the criteria for choosing the predictor variables are the quality of the association between the predictors and the response, and the available predictors at the time of prediction (see also 'ex-ante availability') (Shmueli, 2010). In this dimension (meaning, completeness, and correctness of data (Price & Shanks, 2005, 2008)) it is pertinent to be aware of the limitations of whereby a real-world situation cannot be easily measured due to its non-deterministic or qualitative nature (Bourne, Neely, Mills, & Platts, 2003; Pidun & Felden, 2011). It is necessary to precisely define the target variable (e.g., player performance, team performance, head coach performance, jumping performance, movement efficiency) as well as to consider the limitations of the available indicators (e.g. KPIs) and the lack of unavailable and unknown factors involved in the problem (e.g., player's fatigue is a multifactorial process, which involves physiology, biomechanics, and psychology). Controlling for each factor involved is impossible, hence, one has to select the best available indicators and assume certain limitations).

1.2 *Resolution:* Refers to the measurement scale and aggregation level of the selected input or variable. The measurement scale of the data should be evaluated in terms of its suitability to the goal and the analysis methods to be used. Often higher-resolution data is not feasible due to available resources (e.g. jumping analysis would be more insightful when assessed bilaterally on two force plates, but the organisation can only afford one), but it is also notable that a more granular measurement scale is sometimes associated with more noise. Hence the availability or choice of measurement scale will affect the empirical analysis (e.g., is a 10 Hz GPS sampling rate optimal to assess high-intensity sport-specific movements?). To choose between the multiple measurements, additional information about the reliability and precision of the measuring devices or sources of data is necessary (Kenett & Shmueli, 2016).

1.3 *Structure:* relates to the type(s) of data and data characteristics such as corrupted and missing values (e.g. data sparseness) due to the study design or data collection mechanism. Corrupted and missing values require handling by removal, imputation, data recovery, or other methods. Error values may be treated as missing values when the purpose is to estimate a population parameter, such as in surveys where respondents intentionally enter incorrect responses (Kenett & Shmueli, 2016) (e.g., sometimes wellness questionnaires or rate-of-perceived-exertion have questionable validity when the organisational culture or player buy-in are not adequate).

1.4 *Integration:* Integrating multiple sources and/or types of data often creates new knowledge regarding the targeted task (Kenett & Shmueli, 2016) (e.g., monitoring player's fatigue not just from one variable, but as the integration of or the association between multiple indicators, blood biomarkers, countermovement jump metrics, wellness questionnaire, overall external workloads, etc.). Data integration could also optimize the system's complexity if it reduces data dimensionality (see also Section C.2 on System complexity and parsimony).

1.5 *Data accessibility and timeliness of retrieval:* refers to the ease of data collection, the degree of accessibility to the data from one or multiple sources, and the time it takes to retrieve them. As mentioned in Section A.1.b, to optimize data access and the time of retrieval, a comprehensive and planned data workflow is advisable (Figure 4). Further, a realistic and context-specific data collection process that allows collection of data with minimal interference on the player/team/organization's routines is recommended.

Table 3: Data quality dimensions. Adapted from Kenett et al. (2016).

DATA QUALITY				
MEANING OF DATA (Representativeness)	**DATA RESOLUTION**	**DATA STRUCTURE**	**DATA INTEGRATION**	**ACCESSIBILITY & TIMELINESS**
Input selection	Collection frequency	Missing values	Input integration or association to generate new inputs	Ease of collection
Between-Inputs relationship	Sampling frequency	Corrupted values		Ease of storage
Input meaning or relationship with the problem	Reliability & Precision	Wrong values		Ease of retrieval

2. *System error*

There are three concepts to consider when assessing the DSS' error: precision, accuracy, and bias (Walther & Moore, 2005). Precision is a measure of variance of an estimation procedure, a description of random errors; whereas accuracy is a measure of difference, a description of systematic errors, which represents the overall distance between estimated values and the true value (Walther & Moore, 2005) (to see the relationship between precision, accuracy, and total error see also Section C.2 on 'Model complexity' and Figure 6).

Additionally, any DSS will present some level of inherent bias (i.e., system or algorithm bias) which will have an effect on its accuracy. This is a phenomenon that occurs when a system produces results that are systematically prejudiced due to erroneous assumptions in the analytical processes, or algorithms (Rouse, 2018). The same difficulties humans have in processing and understanding complexity, explained by the theory of *bounded rationality* (Simon, 1956, 1978; Tversky & Kahneman, 1974), can be applied to algorithms. Hence, algorithms performance will be limited by the information they have available (which can be limited and *fallible*), the built-in processes (which may include the developer's *cognitive biases*), and the finite amount of time the system has to produce an output. To overcome this, many algorithms use *heuristics*-based processes that give a 'sufficiently satisfactory result' (a human process known as *satisficing* (Simon, 1956)). Baeza-Yates' taxonomy can be used to identify the different types of computational bias: relating to activity, data, sampling, algorithm, interface, and self-selection (Baeza-Yates, 2016). Based on this taxonomy a DSS developer should assess the three potential bias entry points (Springer, Garcia-Gathright, & Cramer, 2018): data input biases (e.g., due to sample demographics, using only data from on team), processing biases (e.g., from the techniques and the developer's decisions), and outcome interaction biases (e.g., when a recommendation is differently interpreted by two experts, or when the user over-relies or intentionally misuses the system (Parasuraman & Riley, 1997)).

In classification tasks the DSS' error will depend on the number and proportion of misclassified events. Popular techniques to assess error in binary classifiers are *sensitivity* and *specificity*, which respectively represent the ability of a classifier to identify all relevant instances, and to return only relevant ones. The most common means to visualize sensitivity and precision are: the confusion matrix, the receiver operating characteristic (ROC) curve, and the area under the curve (AUC) (Witten et al., 2011). Another popular classification metric is the *Log-Loss*, which specifically penalizes the models' misclassifications.

For DSS incorporating regression-like models, which have a continuous outcome, the error is usually assessed with metrics that measure the magnitude of the difference between the predicted value and the actual value and its variance. Popular methods for such purposes include the Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), R-Squared (R^2), Adjusted R-Squared (R^2), Mean Squared Percentage Error (MSPE), Mean Absolute Percentage Error (MAPE), or the Root Mean Squared Logarithmic Error (RMSLE) (Fortmann-Roe, 2012a; Swalin, 2018; Witten et al., 2011).

There are several other metrics to assess system's error depending on the algorithm to evaluate such as the Rand Index (to assess cluster similarity), the Mutual information (to quantify the mutual dependence between two random variables), the cross-validation error (to assess the model predictive accuracy), or the Bilingual Evaluation Understudy Score or BLEU (to evaluate the quality of machine-translated text) (Fortmann-Roe, 2012a; Swalin, 2018).

Irrespective of whether the outcome is represented continuously or categorically, the abovementioned accuracy measures should also be considered in terms relative to the context of the system use. For instance, in scenarios whereby ongoing implementation of the DSS is anticipated, longitudinal evaluation of its performance is warranted. Acute timespan performance may not be a guarantee of future results. A further contextual consideration in terms of evaluation relates to comparison with existing practice. For instance, a high accuracy DSS that replaces a human decision-making process that is already highly accurate, may not be perceived to be as valuable as in a situation where it replaces an unknown or poor performing scenario.

C. Process Efficiency

The following component focus on evaluating the complexity of the model itself, as well as the data accessibility and timeliness of retrieval, and the decisional guidance (see Sections A.3 and B.1.5, respectively).

1. System complexity

As more parameters are added to a model, its complexity also rises. Thus, its outcome imprecision (or variance) becomes the primary concern while its inaccuracy steadily falls (Fortmann-Roe, 2012b) (Figure 6) (see also Section B.2 on 'System error'). The 'sweet spot' for any model is obtaining a level of complexity at which inaccuracy and imprecision are minimized, while the system is still offering acceptably accurate recommendations. Models in the sweet spot have high explanatory or predictive power with the minimum number of parameters or inputs required, a concept known as parsimony (for more on parsimony see (Kenrose, 2015; Siddall, 2002)).

There is generally a trade-off between system imprecision and inaccuracy as well as between its parsimony and accuracy. Low parsimony models (i.e., models with many parameters) tend to have a better fit, with lower inaccuracy, but higher imprecision, than high parsimony models (Figure 6). Adding more parameters may result in a good model fit for the available data, but the model might be very poor predicting other data sets, this is known as overfitting. Overfitting is the characteristic of an analysis that corresponds too closely or exactly to a particular set of data, and may therefore fail to fit additional data or predict future observations reliably (VV.AA, 2018). An over-fitted model is a model that contains more parameters than can be justified for the given problem (Everitt & Skrondal, 2010). An example of how parsimony could present as a practical problem when assessing a player's team-sport performance: a coach may predominantly consult the player's box score and provide their own rating in evaluating the player; some coaches may like to utilise additional information such as the leadership displayed by their player, or their physical output. Whilst this information does not cover the entirety of components that define the player's performance, adding further variables, may take additional resources and time, for limited improvement in the accuracy of the evaluation. Thus, the most parsimonious decision is to utilise a sub-sample of available metrics, ideally those which display the highest validity. Popular methods to optimize the information gain with the minimum amount of inputs (i.e., parsimony) are: the Akaike's Information Criterion (AIC), the Bayesian Information Criterion (BIC), the Bayes Factor, or the Minimum Description Length (Myung, 2000).

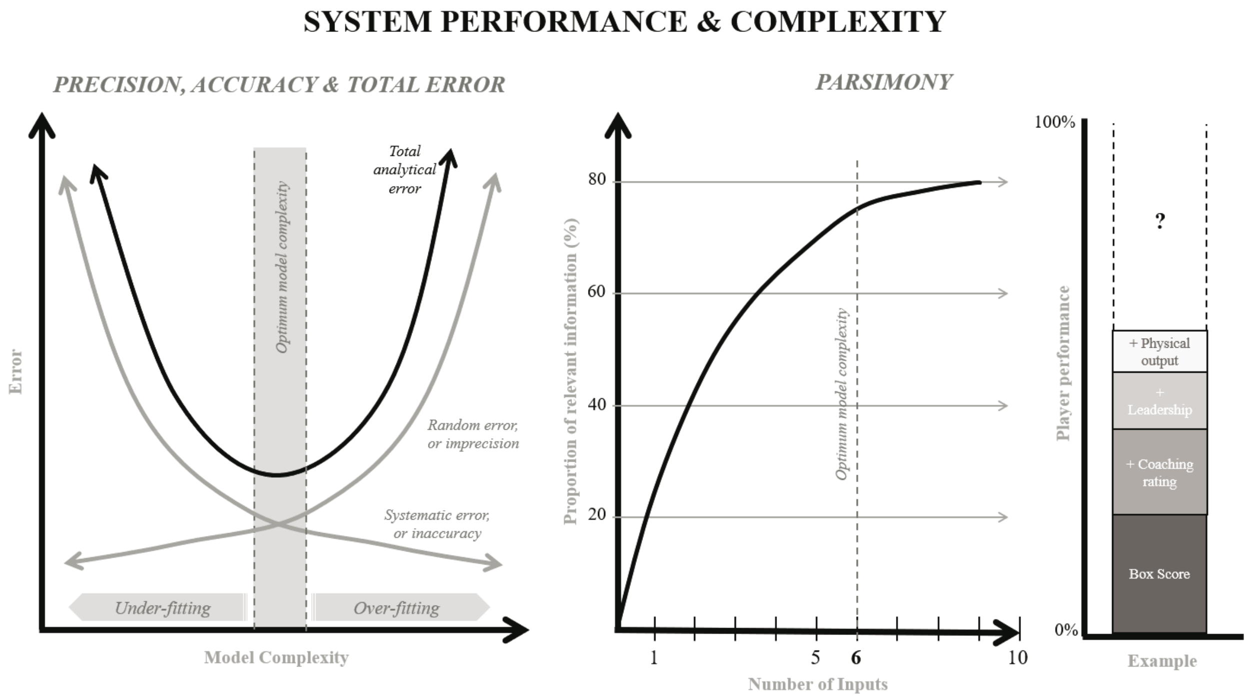

Figure 6: System complexity. Left: relationship between accuracy, precision, and total analytical error (personal adaptation from Fortmann-Roe (2012)). Total analytical error represents the overall System error that is attributed to imprecision (or random errors) and inaccuracy (or systematic errors). Center: Model Parsimony. Optimization of the minimum required number of inputs for maximal information gain. Right: An example of how parsimony could present as a practical problem in the evaluation of a team-sport player's match performance.

Evaluation of Decision Support Systems

The development of a DSS is an iterative process based on problem analysis, design, implementation, and evaluation (Chaudhry, Salchenberger, & Beheshtian, 1996; Sprague, 1980). Hence, the assessment of a DSS should not just focus on its performance, but also on its acceptance (Kayande et al., 2009). Also, when assessing a DSS, solutions from these systems cannot typically be simply assessed in a dichotomous manner (i.e., as right or wrong, or correct or incorrect) (Khazanchi, 1991). This is because the problems a DSS deals with are usually unstructured or semi-structured, and the solutions for these type of problems should be judged as good, bad, or reasonable (Mason & Mitroff, 1973).

Table 4: Decision support system evaluation tool.

DSS EVALUATION TOOL

DSS score = $\sqrt[6]{(C_1 \bullet w_1) \bullet (C_n \bullet w_n) \bullet (C_6 \bullet w_6)}$

Component	Weight	Developer	Expert 1	Expert N
Feasibility	**W_1 [0-1]**	**C_1 [1-5]**	**C_1 [1-5]**	**C_1 [1-5]**
Organizational	-	YES / NO	YES / NO	YES / NO
Technical	-	YES / NO	YES / NO	YES / NO
Financial	-	YES / NO	YES / NO	YES / NO
Legal	-	YES / NO	YES / NO	YES / NO
Delivered knowledge	**W_2 [0-1]**	**C_2 [1-5]**	**C_2 [1-5]**	**C_2 [1-5]**
Usability	-	YES / NO	YES / NO	YES / NO
Decisional guidance	**W_3 [0-1]**	**C_3 [1-5]**	**C_3 [1-5]**	**C_3 [1-5]**
Format (design & visuals)	-	YES / NO	YES / NO	YES / NO
Interaction (mode & invocation)	-	YES / NO	YES / NO	YES / NO
Guidance style (target & directivity)	-	YES / NO	YES / NO	YES / NO
Data quality	**W_4 [0-1]**	**C_4 [1-5]**	**C_4 [1-5]**	**C_4 [1-5]**
Meaning (representativeness)	-	YES / NO	YES / NO	YES / NO
Resolution (sampling & reliability)	-	YES / NO	YES / NO	YES / NO
Structure (sparsity)	-	YES / NO	YES / NO	YES / NO
Accessibility & timeliness	-	YES / NO	YES / NO	YES / NO
System error	**W_5 [0-1]**	**C_5 [1-5]**	**C_5 [1-5]**	**C_5 [1-5]**
Imprecision (random errors)	-	YES / NO	YES / NO	YES / NO
Inaccuracy (systematic errors)	-	YES / NO	YES / NO	YES / NO
Bias (in data input, in processing, in outcome)	-	YES / NO	YES / NO	YES / NO
System complexity	**W_6 [0-1]**	**C_6 [1-5]**	**C_6 [1-5]**	**C_6 [1-5]**
Parsimony	-	YES / NO	YES / NO	YES / NO
Individual DSS Score		Score 1	Score 2	Score N

Conclusions

In any professional field, gaps between practice and evidence can occur when the *expert* develops a pattern of knowledge, which is then relied on for judgments under uncertainty using intuitive processing, without the activation of an analytical alternative obtained from the best available information (Bate et al., 2012; D. Kahneman & Klein, 2009).

In most real-world sport problems it is difficult to trace cause-and-effect relationships between variables because they are too many and they usually exhibit non-linearity. Examples could include the aetiology of many injuries which athletes experience, or quantifying the influence of an individual player's performance on overall team success. Hence, complex problems should be holistically approached, fully engaging experience and intuition as well as analytical processes (Bennet & Bennet, 2008), which can be integrated through decision support systems (DSS).

As the data now being considered in sports environments is increasingly voluminous and beyond human information processing capabilities, the link between decisions and outcomes is often probabilistic or uncertain, or the decisions are repetitive (Kayande et al., 2009). In such environments it is unlikely that decision makers can consistently outperform a DSS (Hoch & Schkade, 1996). Further, the limited utility of decision support systems in sporting contexts to date means that there is a potential for considerable value to be extracted from their application to new scenarios.

This paper contends that the success of a DSS will depend on the understanding of the problem to solve, the context or previous practices in the organization, the available resources, the design and accuracy of the system, and its implementation. In high performance sport, where there is often a risk of a high churn rate with when trialling or adopting new processes, is important that when developing a DSS one should not just focus on its performance, but also its acceptance (Kayande et al., 2009).

The development framework proposed in this paper provides a systematic way to add value to a DSS by ensuring that the proposed components have been considered and optimized before, during, and after developing the system. It provides a framework specifically tailored for us in high-performance sport settings, which has to date not seen attention in the literature. With an increased data volume being generated in high-performance sport from areas such as computer vision and wearable technology, consideration of such data via DSS's will soon likely become a necessity rather than a consideration. Future work should establish the utility and validity of the framework for use in high-performance sport environments.

References

Abut, F., & Akay, M. F. (2015). Machine learning and statistical methods for the prediction of maximal oxygen uptake: recent advances. *Med Devices (Auckl), 8*, 369-379. doi:10.2147/mder.S57281

Adelman, L. (1992). *Evaluating decision support and expert systems*. New York, NY, USA: Wiley-Interscience.

Baeza-Yates, R. (2016). Data and algorithmic bias in the web. *Proceedings of the 8th ACM Conference on Web Science.* Retrieved from https://cacm.acm.org/magazines/2018/6/228035-bias-on-the-web/fulltext

Bartlett, J. D., O'Connor, F., Pitchford, N., Torres-Ronda, L., & Robertson, S. J. (2017). Relationships between internal and external training load in team-sport athletes: evidence for an individualized approach. *Int J Sports Physiol Perform, 12*(2), 230-234. doi:10.1123/ijspp.2015-0791

Bate, L., Hutchinson, A., Underhill, J., & Maskrey, N. (2012). How clinical decisions are made. *Br J Clin Pharmacol, 74*(4), 614-620. doi:10.1111/j.1365-2125.2012.04366.x

Bennet, A., & Bennet, D. (2004). *Organizational survival in the new world: the itelligent complex adaptive system*. Boston: Elsevier.

Bennet, A., & Bennet, D. (2008). *The decision-making process in a complex situation*. Berlin: Springer-Verlag Berlin Heidelberg.

Bertani, A., Cappello, A., Benedetti, M. G., Simoncini, L., & Catani, F. (1999). Flat foot functional evaluation using pattern recognition of ground reaction data. *Clin Biomech (Bristol, Avon), 14*(7), 484-493.

Blythe, D. A., & Kiraly, F. J. (2016). Prediction and quantification of individual athletic performance of runners. *PLoS ONE, 11*(6), e0157257. doi:10.1371/journal.pone.0157257

Bourne, M., Neely, A., Mills, J., & Platts, K. (2003). Implementing performance measurement systems: a literature review. *International Journal of Business Performance Management, 5*(1), 1-24.

Calder, J. M., & Durbach, I. N. (2015). Decision support for evaluating player performance in rugby union. *Int J Sports Sci Coach, 10*(1), 21-37. doi:https://doi.org/10.1260/1747-9541.10.1.21

Carey, D. L., Ong, K., Whiteley, R., Crossley, K. M., Crow, J., & Morris, M. E. (2018). Predictive modelling of training loads and injury in australian football. *International Journal of Computer Science in Sport, 17*(1), 49-66. doi:10.2478/ijcss-2018-0002

Chaudhry, S. S., Salchenberger, L., & Beheshtian, M. (1996). A small business inventory DSS: design development, and implementation issues. *Computers & Operations Research, 23*(1), 63-72. doi:https://doi.org/10.1016/0305-0548(95)00004-6

Chengular-Smith, I. N., Ballou, D., & Pazer, H. L. (1999). The impact of data quality information on decision making: an exploratory analysis. *IEEE Trans. Knowl Data Eng, 11*(6).

Chenoweth, T., L. Dowling, K. L., & St Louis, R. (2004). Convincing DSS users that complex models are worth the effort. *Decision Support Systems, 37*(1), 71-82. doi:10.1016/S0167-9236(03)00005-8

Clermont, C. A., Osis, S. T., Phinyomark, A., & Ferber, R. (2017). Kinematic gait patterns in competitive and recreational runners. *J Appl Biomech, 33*(4), 268-276. doi:10.1123/jab.2016-0218

Croskerry, P. (2005). The theory and practice of clinical decision-making. *Canadian Journal of Anesthesia, 52*(S1), R1–R8.

Croskerry, P. (2009). Context is everything or how could I have been that stupid? *Healthc Q, 12 Spec No Patient*, e171-176.

Donabedian, A. (1980). *Definition of quality and approaches to its assessment*. Ann Arbor, MI: Health Administration Press.

Donabedian, A. (1988). The quality of care. How can it be assessed? *JAMA, 260*(12), 1743-1748. doi:10.1001/jama.260.12.1743

Dutt-Mazumder, A., Button, C., Robins, A., & Bartlett, R. (2011). Neural network modelling and dynamical system theory: are they relevant to study the governing dynamics of association football players? *Sports Med, 41*(12), 1003-1017. doi:10.2165/11593950-000000000-00000

Elragal, A., & Klischewski, R. (2017). Theory-driven or process-driven prediction? Epistemological challenges of big data analytics. *J Big Data, 4*(19). doi:10.1186/s40537-017-0079-2

Ertelt, T., Solomonovs, I., & Gronwald, T. (2018). Enhancement of force patterns classification based on Gaussian distributions. *J Biomech, 67*, 144-149. doi:10.1016/j.jbiomech.2017.12.006

Everitt, B. S., & Skrondal, A. (Eds.). (2010) Cambridge Dictionary of Statistics. Cambridge University Press.

Fisher, C. W., Chengalur-Smith, I., & Ballou, D. P. (2003). The impact of experience and time on the use of data quality information in decision making. *Inform Syst Res, 14*(2), 170−188.

Fortmann-Roe, S. (2012a). Accurately measuring model prediction error. Retrieved from http://scott.fortmann-roe.com/docs/MeasuringError.html

Fortmann-Roe, S. (2012b). Understanding the bias-variance tradeoff. Retrieved from http://scott.fortmann-roe.com/docs/BiasVariance.html

Gönül, M. S., Önkal, D., & Lawrence, M. (2006). The effects of structural characteristics of explanations on use of a DSS. *Decision Support Systems, 42*(3), 1481–1493.

Gregor, S., & Benbasat, I. (1999). Explanations from intelligent systems: theoretical foundations and implications for practice. *MIS Quarterly, 23*(4), 497–530.

Grehaigne, J., Godbout, P., & Bouthier, D. (1997). Performance assessment in team sports. *Journal of Teaching in Physical Education, 16*, 500-516.

Hoch, S. J., & Schkade, D. A. (1996). A psychological approach to decision support systems. *Management Science, 42*(1), 51-64. Retrieved from http://www.jstor.org/stable/2633015

Hogarth, L., Payton, C., Van de Vliet, P., Connick, M., & Burkett, B. (2018). A novel method to guide classification of para swimmers with limb deficiency. *Scand J Med Sci Sports, 28*(11), 2397-2406. doi:10.1111/sms.13229

Hogue, J. T., & Hugh, J. W. (1984). Current practices in the development of decision support systems. *Information and Management*, 205-212. Retrieved from http://aisel.aisnet.org/icis1984/16

Holsapple, C. W. (2008). *Decisions and knowledge*. Berlin: Springer-Verlag Berlin Heidelberg.

Hooshyar, D., Yousefi, M., & Lim, H. (2017). A systematic review of data-driven approaches in player modeling of educational games. *Artificial Intelligence Review, 4*(19), 1-20. doi:doi:10.1007/s10462-017-9609-8

Hunt, D. L., Haynes, R. B., Hanna, S. E., & Smith, K. (1998). Effects of computer-based clinical decision support systems on physician performance and patient outcomes: a systematic review. *JAMA, 280*(15), 1339-1346.

IBM. (2012). IBM SPSS Modeler CRISP-DM Guide. Retrieved from https://www.ibm.com/support/knowledgecenter/en/SS3RA7_15.0.0/com.ibm.spss.crispdm.help/crisp_overview.htm

Janssen, D., Schollhorn, W. I., Newell, K. M., Jager, J. M., Rost, F., & Vehof, K. (2011). Diagnosing fatigue in gait patterns by support vector machines and self-organizing maps. *Hum Mov Sci, 30*(5), 966-975. doi:10.1016/j.humov.2010.08.010

Jaspers, A., De Beeck, T. O., Brink, M. S., Frencken, W. G. P., Staes, F., Davis, J. J., & Helsen, W. F. (2018). Relationships between the external and internal training load in professional soccer: what can we learn from machine learning? *Int J Sports Physiol Perform, 13*(5), 625-630. doi:10.1123/ijspp.2017-0299

Kahneman, D., & Klein, G. (2009). Conditions for intuitive expertise: a failure to disagree. *Am Psychol, 64*(6), 515-526. doi:10.1037/a0016755

Kahneman, D., & Tversky, A. (1979). Prospect theory: an analysis of decision under risk. *Econometrica, 47*(2), 263-292.

Kawamoto, K., Houlihan, C. A., Balas, E. A., & Lobach, D. F. (2005). Improving clinical practice using clinical decision support systems: a systematic review of trials to identify features critical to success. *BMJ, 330*(7494), 765. doi:10.1136/bmj.38398.500764.8F

Kayande, U., De Bruyn, A., Lilien, G. L., Rangaswamy, A., & van Bruggen, G. H. (2009). How incorporating feedback mechanisms in a DSS affects DSS evaluations. *Information Systems Research, 20*(4), 527-546.

Kenett, R., & Shmueli, G. (2016). Dimensions of information quality and InfoQ assessment. In R. Kenett & G. Shmueli (Eds.), *The Potential of Data and Analytics to Generate Knowledge*. Chichester, West Sussex: WILEY.

Kenrose, S. (2015). Parsimonious model: definition, ways to compare models. *Statistics How To.* Retrieved from https://www.statisticshowto.datasciencecentral.com/parsimonious-model/

Khazanchi, D. (1991). *Evaluating decision support systems: a dialectical perspective.* Paper presented at the 24th Annual Hawaii International Conference on Systems Sciences (HICSS-24), Hawaii.

Kianifar, R., Lee, A., Raina, S., & Kulic, D. (2016). Classification of squat quality with inertial measurement units in the single leg squat mobility test. *Conf Proc IEEE Eng Med Biol Soc, 2016*, 6273-6276. doi:10.1109/embc.2016.7592162

Kipp, K., Giordanelli, M., & Geiser, C. (2018). Predicting net joint moments during a weightlifting exercise with a neural network model. *J Biomech, 74*, 225-229. doi:10.1016/j.jbiomech.2018.04.021

Kovalchik, S., & Reid, M. (2018). A shot taxonomy in the era of tracking data in professional tennis. *J Sports Sci, 36*(18), 2096-2104. doi:10.1080/02640414.2018.1438094

Lai, F., Macmillan, J., Daudelin, D. H., & Kent, D. M. (2006). The potential of training to increase acceptance and use of computerized decision support systems for medical diagnosis. *Hum Factors, 48*(1), 95-108. doi:10.1518/001872006776412306

Lai, M., Meo, R., Schifanella, R., & Sulis, E. (2018). The role of the network of matches on predicting success in table tennis. *J Sports Sci*, 1-8. doi:10.1080/02640414.2018.1482813

Leicht, A. S., Gomez, M. A., & Woods, C. T. (2017). Explaining match outcome during the men's basketball tournament at the olympic games. *J Sports Sci Med, 16*(4), 468-473.

Li, X., Huang, H., Wang, J., Yu, Y., & Ao, Y. (2016). The analysis of plantar pressure data based on multimodel method in patients with anterior cruciate ligament deficiency during walking. *Biomed Res Int, 2016*, 7891407. doi:10.1155/2016/7891407

Limayem, M., & DeSanctis, G. (2000). Providing decisional guidance for multicriteria decision making in groups. *Information Systems Research, 11*(4), 386-401. Retrieved from http://www.jstor.org/stable/23011044

Link, D., & Hoernig, M. (2017). Individual ball possession in soccer. *PLoS ONE, 12*(7), e0179953. doi:10.1371/journal.pone.0179953

Lopez-Valenciano, A., Ayala, F., Puerta, J. M., MBA, D. E. S. C., Vera-Garcia, F. J., Hernandez-Sanchez, S., . . . Myer, G. D. (2018). A preventive model for muscle injuries: a novel approach based on learning algorithms. *Med Sci Sports Exerc, 50*(5), 915-927. doi:10.1249/mss.0000000000001535

MacMahon, C., & McPherson, S. L. (2009). Knowledge base as a mechanism for perceptual-cognitive tasks: skill is in the details! *International Journal of Sport Psychology, 40*, 565–579.

Maier, T., Meister, D., Trosch, S., & Wehrlin, J. P. (2018). Predicting biathlon shooting performance using machine learning. *J Sports Sci*, 1-7. doi:10.1080/02640414.2018.1455261

Makridakis, S., Kirkham, R., Wakefield, A., Papadaki, M., Kirkham, J., & Long, L. (2019). Forecasting, uncertainty and risk; perspectives on clinical decision-making in preventive and curative medicine. *International Journal of Forecasting, 35*(2), 659-666. doi:https://doi.org/10.1016/j.ijforecast.2017.11.003

Maselli, A., Dhawan, A., Cesqui, B., Russo, M., Lacquaniti, F., & d'Avella, A. (2017). Where are you throwing the ball? I better watch your body, not just your arm! *Front Hum Neurosci, 11*, 505. doi:10.3389/fnhum.2017.00505

Mason, R. O., & Mitroff, I. I. (1973). A program for research on management information systems. *Manage Sci, 19*(5), 475−487.

Mawhinney, C. H., & Lederer, A. L. (1990). A study of personal computer utilization by managers. *Information & mangement, 18*(5), 243-253.

McNichol, D. (2018). On average, you're using the wrong average: geometric & harmonic means in data analysis. Retrieved from https://towardsdatascience.com/on-average-youre-using-the-wrong-average-geometric-harmonic-means-in-data-analysis-2a703e21ea0

Montazemi, A. R., Wang, F., Khalid Nainara, S. M., & Barta, C. K. (1996). On the effectiveness of decisional guidance. *Decision Support Systems, 18*(2), 181-198. doi:10.1016/0167-9236(96)00038-3

Montgomery, A. (2005). The implementation challenge of pricing decision support systems for retail managers. *Appl Stochastic Models Bus Indust, 27*(4-5), 367-378.

Montoliu, R., Martin-Felez, R., Torres-Sospedra, J., & Martinez-Uso, A. (2015). Team activity recognition in association football using a bag-of-words-based method. *Hum Mov Sci, 41*, 165-178. doi:10.1016/j.humov.2015.03.007

Morana, S., Schacht, S., Scherp, A., & Maedche, A. (2014). Conceptualization and typology of guidance in information systems. *Working Paper Series in Information Systems. University of Mannheim., 7*, 1-13.

Morgulev, E., & Galily, Y. (2018). Choking or delivering under pressure? the case of elimination games in NBA playoffs. *Front Psychol, 9*(979). doi:10.3389/fpsyg.2018.00979

Myung, I. J. (2000). The importance of complexity in model selection. *J Math Psychol, 44*(1), 190-204. doi:10.1006/jmps.1999.1283

Nagata, T., Nakamura, N., Miyatake, M., Yuuki, A., Yomo, H., Kawabata, T., & Hara, S. (2016). VO2 estimation using 6-axis motion sensor with sports activity classification. *Conf Proc IEEE Eng Med Biol Soc, 2016*, 4735-4738. doi:10.1109/embc.2016.7591785

Novatchkov, H., & Baca, A. (2013). Artificial intelligence in sports on the example of weight training. *J Sports Sci Med, 12*(1), 27-37.

Ofoghi, B., Zeleznikow, J., Macmahon, C., & Dwyer, D. (2013). Supporting athlete selection and strategic planning in track cycling omnium: A statistical and machine learning approach. *Inf. Sci., 233*, 200-213. doi:10.1016/j.ins.2012.12.050

Ofoghi, B., Zeleznikow, J., Macmahon, C., Rehula, J., & Dwyer, D. B. (2016). Performance analysis and prediction in triathlon. *J Sports Sci, 34*(7), 607-612. doi:10.1080/02640414.2015.1065341

Olade, R. A. (2004). Strategic collaborative model for evidence-based nursing practice. *Worldviews Evid Based Nurs, 1*(1), 60-68. doi:10.1111/j.1741-6787.2004.04003.x

Parasuraman, R., & Riley, V. (1997). Humans and automation: use, misuse, disuse, abuse. *Human Factors: The Journal of the Human Factors and Ergonomics Society, 39*(2), 230-253.

Parikh, M., Fazlollahi, B., & Verma, S. (2001). The effectiveness of decisional guidance: an empirical evaluation. *Decision Sciences, 32*(2), 303-332. doi:10.1111/j.1540-5915.2001.tb00962.x

Pernek, I., Kurillo, G., Stiglic, G., & Bajcsy, R. (2015). Recognizing the intensity of strength training exercises with wearable sensors. *J Biomed Inform, 58*, 145-155. doi:10.1016/j.jbi.2015.09.020

Pidun, T., & Felden, C. (2011). *Limitations of performance measurement systems based on key performance indicators.* Paper presented at the AMCIS.

Plous, S. (1993). *The psychology of judgment and decision Making*. New York: McGraw-Hill.

Price, R., & Shanks, G. (2005). A semiotic information quality framework fevelopment and comparative analysis. *Journal of Information Technology, 20*(2), 88-102. doi:https://doi.org/10.1057/palgrave.jit.2000038

Price, R., & Shanks, G. (2008). Data quality and decision making. In F. Burstein & C. W. Holsapple (Eds.), *Handbook on Decision Support Systems*: Springer-Verlag Berlin Heidelberg.

Redman, T. (1997). Improve data quality for competitive advantage. *Sloan Manag Rev, 36*(2), 99−107.

Rein, R., & Memmert, D. (2016). Big data and tactical analysis in elite soccer: future challenges and opportunities for sports science. *Springerplus, 5*(1), 1410. doi:10.1186/s40064-016-3108-2

Rhee, C., & Rao, H. R. (2008). Evaluation of decision support systems. In F. Burstein & C. W. Holsapple (Eds.), *Handbook on Decision Support Systems*: Springer-Verlag Berlin Heidelberg.

Ribeiro, M. T., Singh, S., & Guestrin, C. (2016). *Why should i trust you?: explaining the predictions of any classifier.* Paper presented at the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining.

Richter, C., King, E., Falvey, E., & Franklyn-Miller, A. (2018). Supervised learning techniques and their ability to classify a change of direction task strategy using kinematic and kinetic features. *J Biomech, 66*, 1-9. doi:10.1016/j.jbiomech.2017.10.025

Rindal, O. M. H., Seeberg, T. M., Tjonnas, J., Haugnes, P., & Sandbakk, O. (2017). Automatic classification of sub-techniques in classical cross-country skiing using a machine learning algorithm on micro-sensor data. *Sensors (Basel), 18*(1). doi:10.3390/s18010075

Robertson, S., Bartlett, J. D., & Gastin, P. B. (2016). Red, amber or green? athlete monitoring in team sport: the need for decision support systems. *Int J Sports Physiol Perform*, 1-24. doi:10.1123/ijspp.2016-0541

Robertson, S., & Joyce, D. (2018). Evaluating strategic periodisation in team sport. *J Sports Sci, 36*(3), 279-285. doi:10.1080/02640414.2017.1300315

Robertson, S. J., & Joyce, D. G. (2015). Informing in-season tactical periodisation in team sport: development of a match difficulty index for Super Rugby. *J Sports Sci, 33*(1), 99-107. doi:10.1080/02640414.2014.925572

Rossi, A., Pappalardo, L., Cintia, P., Iaia, F. M., Fernandez, J., & Medina, D. (2018). Effective injury forecasting in soccer with GPS training data and machine learning. *PLoS ONE, 13*(7), e0201264. doi:10.1371/journal.pone.0201264

Rouse, M. (2018). Machine learning bias (algorithm bias or AI bias). Retrieved from https://searchenterpriseai.techtarget.com/definition/machine-learning-bias-algorithm-bias-or-AI-bias

Ruddy, J. D., Shield, A. J., Maniar, N., Williams, M. D., Duhig, S., Timmins, R. G., . . . Opar, D. A. (2018). Predictive modeling of hamstring strain injuries in elite australian footballers. *Med Sci Sports Exerc, 50*(5), 906-914. doi:10.1249/mss.0000000000001527

Safdar, S., Zafar, S., Zafar, N., & Khan, N. F. (2017). Machine learning based decision support systems (DSS) for heart disease diagnosis: a review. *Artificial Intelligence Review*, 1-27.

Sampaio, J., McGarry, T., Calleja-Gonzalez, J., Jimenez Saiz, S., Schelling, X., & Balciunas, M. (2015). Exploring game performance in the National Basketball Association using player tracking data. *PLoS ONE, 10*(7), e0132894. doi:10.1371/journal.pone.0132894

Sanders, N. R., & Manrodt, K. B. (2003). Forecasting software in practice: use, satisfaction, and performance. *Interfaces, 33*(5), 90-93. Retrieved from http://www.jstor.org/stable/20141289

Shmueli, G. (2010). To explain or to predict? *Statistical Science, 25*(3), 289-310. doi:10.1214/10-sts330

Siddall, M. E. (2002). Parsimony analysis. In R. DeSalle, G. Giribet, & W. Wheeler (Eds.), *Techniques in Molecular Systematics and Evolution. Methods and Tools in Biosciences and Medicine.* Basel: Birkhäuser.

Silver, M. (2006). Decisional guidance. Broadening the scope. *Advances in Management Information Systems, 6*, 90–119.

Silver, M. S. (1991). Decision guidance for computer based decision support. *MIS Quart, 15*(105-122).

Silver, M. S. (2008). On the design features of decision support systems: the role of system restrictiveness and decisional guidance. In F. Burstein & C. W. Holsapple (Eds.), *Handbook on Decision Support Systems*: Springer-Verlag Berlin Heidelberg.

Simon, H. A. (1956). Rational Choice and the Structure of the Environment. *Psychological Review, 63*(2), 129–138.

Simon, H. A. (1978). Rational decision-making in business organizations. Nobel memorial lecture. Retrieved from http://nobelprize.org/nobel_prizes/economics/laureates/1978/simon-lecture.pdf

Sprague, R. H. (1980). A framework for the development of decision support systems. *MIS Quarterly, 4*(4), 1-26.

Springer, A., Garcia-Gathright, J., & Cramer, H. (2018). *Assessing and addressing algorithmic bias — but before we get there*. Paper presented at the 2018 AAAI Spring Symposium Series, Stanford University. https://www.aaai.org/ocs/index.php/SSS/SSS18/paper/viewFile/17542/15470

Swalin, A. (2018). Choosing the right metric for evaluating machine learning models—Part 1. Retrieved from https://medium.com/usf-msds/choosing-the-right-metric-for-machine-learning-models-part-1-a99d7d7414e4

Taha, Z., Musa, R. M., Abdul Majeed, A., Alim, M. M., & Abdullah, M. R. (2018). The identification of high potential archers based on fitness and motor ability variables: A Support Vector Machine approach. *Hum Mov Sci, 57*, 184-193. doi:10.1016/j.humov.2017.12.008

Thornton, H. R., Delaney, J. A., Duthie, G. M., & Dascombe, B. J. (2017). Importance of various training-load measures in injury incidence of professional rugby league athletes. *Int J Sports Physiol Perform, 12*(6), 819-824. doi:10.1123/ijspp.2016-0326

Torres-Ronda, L., & Schelling, X. (2017). Critical process for the implementation of technology in sport organizations. *Strength and Conditioning Journal, 39*(6), 54-59. doi:10.1519/ssc.0000000000000339

Tversky, A., & Kahneman, D. (1974). Judgment under uncertainty: heuristics and biases. *Science, 185*(4157), 1124-1131. doi:10.1126/science.185.4157.1124

Valatavičius, A., & Gudas, S. (2017). Towards the deep, knowledge-based interoperability of applications. *Informacijos Mokslai, 79*, 83-113.

VV.AA. (2018). OxfordDictionaries.com. Retrieved from https://en.oxforddictionaries.com/definition/overfitting

Wali Van Lohuizen, C. W. (1986). Knowledge management and policymaking. *Knowledge, 8*(1), 12-38. doi:10.1177/107554708600800102

Walther, B. A., & Moore, J. L. (2005). The concepts of bias, precision and accuracy, and their use in testing the performance of species richness estimators, with a literature review of estimator performance. *Ecography, 28*, 815-829.

Whiteside, D., Cant, O., Connolly, M., & Reid, M. (2017). Monitoring hitting load in tennis using inertial sensors and machine learning. *Int J Sports Physiol Perform, 12*(9), 1212-1217. doi:10.1123/ijspp.2016-0683

Whiteside, D., & Reid, M. (2017). Spatial characteristics of professional tennis serves with implications for serving aces: A machine learning approach. *J Sports Sci, 35*(7), 648-654. doi:10.1080/02640414.2016.1183805

Witten, I. A., Frank, E., & Hall, M. A. (2011). *Data mining. Practical machine learning tools and techniques* (Third ed.). Burlington, Massachussetts, USA.: Elsevier.

Woods, C. T., Veale, J., Fransen, J., Robertson, S., & Collier, N. F. (2018). Classification of playing position in elite junior Australian football using technical skill indicators. *J Sports Sci, 36*(1), 97-103. doi:10.1080/02640414.2017.1282621

Wundersitz, D. W., Josman, C., Gupta, R., Netto, K. J., Gastin, P. B., & Robertson, S. (2015). Classification of team sport activities using a single wearable tracking device. *J Biomech, 48*(15), 3975-3981. doi:10.1016/j.jbiomech.2015.09.015

Xie, J., Xu, J., Nie, C., & Nie, Q. (2017). Machine learning of swimming data via wisdom of crowd and regression analysis. *Math Biosci Eng, 14*(2), 511-527. doi:10.3934/mbe.2017031

Zhang, J., Lockhart, T. E., & Soangra, R. (2014). Classifying lower extremity muscle fatigue during walking using machine learning and inertial sensors. *Ann Biomed Eng, 42*(3), 600-612. doi:10.1007/s10439-013-0917-0