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*Red, Amber, or Green? Athlete Monitoring in Team Sport: The Need for Decision-Support Systems*

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1 **Red, amber or green? Athlete monitoring in team sport: the need for decision support**  
2 **systems**

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18 **Running head: Decision support systems in team sports**

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## **Abstract**

Decision support systems are used in team sport for a variety of purposes including evaluating individual performance and informing athlete selection. A particularly common form of decision support is the traffic light system, where colour coding is used to indicate a given status of an athlete with respect to performance or training availability. However despite relatively widespread use, there remains a lack of standardisation with respect to how traffic light systems are operationalised. This paper addresses a range of pertinent issues for practitioners relating to the practice of traffic light monitoring in team sports. Specifically, the types and formats of data incorporated in such systems are discussed, along with the various analysis approaches available. Considerations relating to the visualisation and communication of results to key stakeholders in the team sport environment are also presented. In order for the efficacy of traffic light systems to be improved, future iterations should look to incorporate the recommendations made here.

**Key words:** load, training, physical performance, injury

## 1 Introduction

2 Decision support systems are computer-based information systems that provide objective  
3 evidence relating to the decision-making of organisations.<sup>[1]</sup> Such systems utilise historical  
4 data to generate a recommendation or assessment to a user, with the decision often provided  
5 based on output generated by a software-based algorithm.<sup>[2,3]</sup> In sport, decision support  
6 systems have been used for purposes such as tournament scheduling,<sup>[4]</sup> evaluating athlete  
7 performance<sup>[5]</sup> and informing team selection.<sup>[6]</sup> A number of challenges are required to be  
8 overcome in order for decision support systems to provide ongoing value to organisations.  
9 These include a willingness of users to accept and act on findings/recommendations,  
10 appropriate integration of the system into the organisation's workflow as well as ensuring  
11 consistent use by practitioners.<sup>[7]</sup> Although evidence supporting their use is to date equivocal  
12 (see <sup>[8-9]</sup> for examples of unsuccessful implementations), relative success in fields such as  
13 medicine <sup>[2,3]</sup> make decision support systems an attractive proposition for sporting  
14 organisations in managing recent increases in data generation.

15 In team sports, one form of decision support, 'traffic light systems' are becoming more  
16 popular in their use to inform and support the decisions of practitioners. Although the nature  
17 of these decisions may vary, they often relate to the type and level of training an athlete is to  
18 undertake, or their availability to participate in competition. Also used to monitor student  
19 progress in education,<sup>[10]</sup> traffic light systems function by flagging red, amber or green,  
20 thereby providing a rapid insight into how different from the norm a daily score is for a given  
21 measurement. For instance, green may be interpreted as things should continue as per normal,  
22 amber suggests caution that if left unattended could pose a risk, whilst red raises an alarm and  
23 indicates action is required in order to bring the response back closer to the norm.  
24 Considering the constraints, time-pressures and challenges that practitioners face in the day-

25 to-day fast paced environment of high performance sport, the ease of application, visual  
26 appeal and translational ability of the traffic light approach make them an attractive option in  
27 applied sporting environments. Nevertheless, evidence of their basis as an objective decision  
28 support system is scarce.

29 In performance sport contexts, measurements used in the traffic light systems are often  
30 derived directly from the athlete (both subjective and objective data), with the evidence base  
31 built using historical data. Types of data considered by practitioners using traffic light  
32 systems include self-reported athlete wellness, <sup>[11]</sup> musculoskeletal screening scores, <sup>[12]</sup>  
33 training load, <sup>[13]</sup> fitness and fatigue <sup>[14]</sup> and physiological testing/benchmarking. <sup>[15]</sup>  
34 Typically, users will use this information to adjust training programs and/or treatment in an  
35 effort to avoid undertraining/overtraining, reduce the likelihood of injury/illness incidence  
36 and determine the effectiveness of training programmes to ensure maintenance of  
37 performance. <sup>[16]</sup>

38

### 39 *Validating the decision not to train*

40 One of the most common outputs of traffic light systems used in a decision support context  
41 relates to a determination on the volume and intensity of training an athlete will undertake for  
42 a given session (or period of time). A common issue with traffic light systems is that it is  
43 often not clear what is used to validate the decision to restrict an athlete's training. A number  
44 of problems arise when these systems are attempted to be validated, especially when using  
45 either injury prevention and/or performance-based metrics.

46 For instance, individual player performance as a construct has proved difficult to define in  
47 team sports; due largely in part to the multifaceted nature of game play. <sup>[17]</sup> Further,  
48 considerable individual performance variation is likely to be observed depending on what is

49 occurring at the team level. <sup>[18]</sup> Using injury incidence as a measure is no less problematic. As  
50 injury occurs at such a low incidence relative to the total number of sessions/matches players  
51 participate in, any decision support system for training availability is almost certainly destined  
52 to be conservative in its approach. The implications of this is that athletes may be missing  
53 sessions that they may participate in without adverse effect, thereby exerting a flow on effect  
54 to performance.

55 Another fundamental problem with both forms of data is that access to injury or individual  
56 performance information is not available prior to the training session or match of interest. As  
57 such, traffic light systems in their current format are limited as a *predictive* tool. All they can  
58 do is (partially?) *explain* why an injury did or did not occur, or why a player did or did not  
59 perform to their usual standard (see Shmueli, 2010 <sup>[19]</sup> for a description of the differences  
60 between explanation and prediction). Of course that is of limited use to a practitioner making  
61 decisions on the athlete's availability. Further, in order to make an accurate prediction based  
62 on historical data, a large number of data points are required, which necessitates a long lead  
63 in time and therefore limits those in the early stages of implementing a monitoring program.  
64 Consequently, proxies for under-recovery or susceptibility to injury, derived from the  
65 literature and or practitioner experience, are used as early warning signs for decision making  
66 with the intent to mitigate the risk of an undesirable outcome. So how can the evidence  
67 behind traffic light methods be improved, without losing the practical qualities that make  
68 them so popular in the first place?

69 Despite the abovementioned methodological issues pertaining to injury prediction,  
70 nonetheless there has been a range of research investigating the relationships between the  
71 incidence of injury with player wellness, <sup>[20]</sup> musculoskeletal screening test scores, <sup>[21]</sup> fitness  
72 levels <sup>[22]</sup> and training load. <sup>[23]</sup> As many elite team sport athletes are being assessed in some  
73 capacity on an almost daily basis, the ability to analyse these athletes at the individual level

74 has never been more feasible. The rise in popularity of data mining in sport <sup>[24]</sup> has also  
75 allowed for non-linear relationships between load metrics <sup>[25]</sup> and injury/performance <sup>[26]</sup> at  
76 the inter- and intra-individual level to be better elucidated and visualised. Consequently, it is  
77 evident that in order to obtain better answers to these questions, both large data sets and  
78 complex analyses are required. The benefits of improving objective decision support systems  
79 such as traffic lights are important to both the performance and financial health of sports  
80 organisations. Below we provide some guiding principles for practitioners that can help to  
81 improve the efficacy of the approach.

82

### 83 **Step 1 – What type of data should be considered in the traffic light system?**

84 Collecting, maintaining and analysing the types of data mentioned earlier has in many sports  
85 become a full-time job in itself. For the sports practitioner, reducing the volume of data to  
86 consider in making a decision on an athlete's training availability or determining their injury  
87 risk can greatly increase work efficiency. A pertinent example relating to data reduction can  
88 be drawn from Bartlett et al., 2016 <sup>[25]</sup> where the authors investigated the relationships  
89 between commonly collected training metrics and the session RPE response of athletes at a  
90 professional Australian Rules Football club. It was observed that the relationship between the  
91 distance covered by an individual in a session and the training time was almost a perfect one.  
92 Consequently, as is standard practice in relationship modelling <sup>[27]</sup> one of these metrics  
93 (training time) was removed from the model; in this case without any meaningful adverse  
94 effect on accuracy. Of course the data reduction could have instead been applied to the  
95 second metric. The duration of a training session is easier to measure than the distance an  
96 athlete has covered, which is of practical use to those without access to GPS or other player  
97 tracking systems. Amongst other benefits, the practice of data reduction helps to improve

98 model parsimony, which in the event of multiple solutions existing to a single problem the  
99 simplest should be chosen (see Coutts' 2014 editorial on the relevance of Occam's Razor to  
100 sport science<sup>[28]</sup>).

101 So which considerations, in addition to the above, can help the practitioner to arrive at a  
102 decision on what to look at and what to leave out when designing their traffic light system?  
103 Figure 1 shows five main factors that should be considered by those working in high-level  
104 team sport environments, with an outline of each provided below.

105

106 \*\*\*\*\* INSERT FIGURE 1 ABOUT HERE \*\*\*\*\*

107

#### 108 *Validity of measurements and data entry*

109 The validity of a measure or the strength of relationships between variables of interest should  
110 primarily inform the decision support system. For instance, concurrent validity refers to the  
111 extent to which a metric relates to an alternate, previously validated measure of the same  
112 construct administered at the same time (e.g., assessing training time and distance covered as  
113 per the example above).<sup>[29]</sup> Convergent validity relates to the extent to which two metrics  
114 that theoretically should be related to each other are, indeed, related to each other (e.g., an  
115 increase in heart rate as the intensity of a training session also increases).<sup>[30]</sup> As an example,  
116 if certain information relating to activities the player undertook the night before a training  
117 session showed limited relationship with the athlete's risk of injury or performance in  
118 competition, it would not make sense to measure it for that purpose. In the context of  
119 designing a traffic light system, an assessment of these forms of validity is essentially another  
120 form of the data reduction process. Whilst these and other forms of validity are not always



121 measurable or relevant for all metrics included in the traffic light system, they should be  
122 assessed wherever possible. Alternately, a review of the literature can inform the approach,  
123 via evaluation of the suitability of both objective and subjective measures <sup>[31]</sup> and  
124 consideration of issues related to sport context and implementation. <sup>[32]</sup>

125         Of equal importance is consideration of the reliability of a traffic light system. Some  
126 level of random error is inherent and to be expected in any measurement. From a systematic  
127 perspective if technology shows meaningful differences between different devices, units or  
128 software versions or the methods of obtaining self-report data change, <sup>[33]</sup> then reliability will  
129 in turn also be affected. Therefore, this within- and between-athlete variability should be  
130 accounted for. With sufficient data, the latter consideration can be overcome through the  
131 development of separate models for each individual athlete.

### 132 *Data interpretation and decision-making consequences*

133 In professional team sports, where decisions relating to training availability need to be made  
134 within 1-2 hrs of training commencing, the traffic light system needs to be easily and quickly  
135 interpretable. Whilst coaches are expected to be learned and experienced in their content area,  
136 they are typically not statistically trained. Consequently, more sophisticated data formats may  
137 require conversion before being communicated to coaches and other practitioners. For  
138 instance, raw data may need to be converted to a normalised score (e.g., a z-score) to allow  
139 historical intra-individual or within-team, sport or gender comparisons. <sup>[34]</sup> Often this will  
140 also entail some form of visualisation, which may also vary in nature depending on the  
141 preferences or learning styles of the intended audience. Delivery flexibility and the ability to  
142 generate visualisations rapidly are crucial in ensuring all stakeholders can interpret results for  
143 their given use. *Cost effectiveness*

144 The cost effectiveness of a system includes features such as burden, time and cost/benefit. In  
145 its most simple form, burden relates to the number of staff and the resources required in order  
146 to collect, clean, interpret and report the data used in the traffic light system. This includes  
147 both the start-up cost (e.g., hardware and software, data storage solutions) and daily operation  
148 of the measurement system. Many companies working in elite sport have aimed to provide  
149 user-friendly software in order to expedite this process. However, if metrics of interest are not  
150 reported by the accompanying software, then further post-hoc analysis of raw data may be  
151 required. Burden can also exist in the form of staff being required to undertake further  
152 training in order to complete the collection and analysis of data. This may also extend to their  
153 ability to understand and interpret any results derived from these analyses. In addition, the  
154 burden on the athlete should also be considered and minimised as much as possible. <sup>[32]</sup>

155 Closely linked with interpretability and burden, the time required to collect, interpret and  
156 report is paramount to a successful, useful and meaningful decision support system. How  
157 much time it takes to manage data and implement a decision support system (especially in the  
158 context where thousands of observations can be obtained in one week for a single team)  
159 dictates the success of a given system. For example, analysing a continuous trace of 10 Hz  
160 GPS data for each player for each training session can allow for interesting insights into the  
161 movement of athletes, however, it can be time consuming. Consequently, the extent to which  
162 gaining this insight provides added benefit to informing a decision comparative to the time  
163 spent on the analysis needs to be examined.

164 In high-level sport, the decision support system should be considered in relation to its cost  
165 and benefit so as to determine its efficacy and value to an overall programme. Beyond the  
166 more tangible benefits such as possible improvements in performance and reductions in  
167 injuries and illnesses, other benefits such as communication between staff and athletes,

168 building knowledge within the programme and supporting athlete self-management are all  
169 possible benefits of developing monitoring and decision support systems. <sup>[35]</sup>

170

## 171 **Step 2 – In which format should traffic light system data be analysed?**

172 The format in which data are analysed can alter the nature of the inferences made,  
173 irrespective of the analysis approach implemented. Whilst ideal where possible, the analysis  
174 of unconverted, raw data can result in substantially varied baseline values across different  
175 athletes, making between-individual comparisons challenging. As a result, in team sport  
176 settings z-scores continue to experience popularity based on their ability to allow for the  
177 standardised position of an individual within a group or with reference to their own baseline  
178 data to be articulated. Expressing data as a percentage change from baseline addresses this by  
179 allowing for the within-individual differences to be interpreted within context of others in the  
180 group. However where large within-individual variation exists in data, or where values are  
181 close to zero, artificially high values may result. Furthermore, the conversion of the data to a  
182 relative format may be less interpretable to some stakeholders. So which format should be  
183 used in traffic light systems? One of the key considerations in making this selection relates to  
184 the decision to focus on the individual or the group.

### 185 *Individual vs group*

186 The importance of considering the individual within a team has received increased attention  
187 of late. <sup>[25,36]</sup> However, it is well established that analysing larger numbers of athletes together  
188 can allow for greater inferences to be made relating to the sample population of interest,  
189 thereby increasing the confidence in such findings. <sup>[37]</sup> The approach taken is likely to depend  
190 on the question at hand. For instance, when considering a team sport training scenario, a

191 typical approach for practitioners would be to use within-group comparisons and literature to  
192 determine the typical responses for a given training period. Figure 2 provides an example of a  
193 practical problem with this approach. The figure shows the average weekly training load for  
194 39 players from an Australian Football League club over the course of a month during the  
195 season. Both weekly mean values and the variance differs substantially between players, thus  
196 the need for an individual approach is self-evident.

197

198 \*\*\*\* INSERT FIGURE 2 ABOUT HERE \*\*\*\*

199

### 200 **Step 3 – How is traffic light data analysed and interpreted?**

201 The consideration on whether to assess at the individual or group level will also have direct  
202 implications for the types of analysis undertaken. A range of commentaries and resources  
203 exist relating to the various approaches available to sport scientists. <sup>[38-39]</sup> However, perhaps  
204 the two most pervasive topics relate to determining what constitutes a meaningful change and  
205 the accounting for repeated measures in analyses.

#### 206 *Accounting for repeated measures*

207 Most traffic light systems will incorporate repeated measures data. Many of these  
208 measurements occur on a daily basis; aggregated weekly or monthly values along with rolling  
209 averages are often then calculated to describe trends in the data as well as facilitate analysis.  
210 However, when group data is pooled without account for the dependency of repeated  
211 observations on the same individual/s, relationships between variables of interest can be  
212 overstated. <sup>[40]</sup> Generalised linear models such as linear mixed models and generalised  
213 estimating equations can account for this issue in the modelling process, however whilst

214 relatively common in research, their use may require upskilling of practitioners. Although  
215 machine learning algorithms can allow for any potential non-linearity both between and  
216 within individuals to be uncovered, most approaches assume independence between  
217 observations. The development of models for each individual has been used as another  
218 method of avoiding the repeated measures issue. <sup>[25]</sup> However this will be more time  
219 consuming when large player numbers are involved. Further, in instances where limited data  
220 exists obtaining a well-fit model also may become a challenge.

221

### 222 *Identifying a meaningful change*

223 In sporting terms, it is important to identify what longitudinal changes in responses (i.e., to  
224 training) are meaningful, above and beyond ‘normal’ or random variability. Given the  
225 historical records of data now available to many professional teams, a number of approaches  
226 have been proposed in the literature to determine what constitutes a ‘meaningful’ change  
227 (often referred to as responsiveness). <sup>[41]</sup> The standard deviation (SD), effect size, smallest  
228 worthwhile change (SWC), coefficient of variation (CV) and risk ratio are just some  
229 examples of metrics used to determine this meaningful change. However, unsurprisingly each  
230 measure will provide different outputs.

231

232 \*\*\*\*\* INSERT TABLE 1 & FIGURE 3 ABOUT HERE \*\*\*\*\*

233

234 In the Figure 2 example, despite similar weekly mean training loads, the distinct levels of  
235 variance between each player results in substantially different thresholds for each player,  
236 therefore also resulting in different flags (Table 1). Table 1 shows an example of a traffic

237 light system in operation. In this illustration a  $< 0.3 \times CV$  of the weekly load is considered  
238 'green' (a 'small' effect/difference), a  $0.3$  to  $0.9 \times CV$  equates to 'amber' (a 'moderate'  
239 difference) and a  $0.9$  to  $1.6 \times CV$  is 'red' (a large difference). It should be noted that this  
240 approach represents only one example and a variety of others experience use in the field.  
241 Such systems have clear implications for decision-making between individuals within a  
242 group. Clearly if one traffic light system was calibrated using a CV approach, and another  
243 using the SD, then the measurement and observation would be different, therefore, triggering  
244 a different course of follow up action. In complement to Figure 2, Figure 3 displays the  
245 weekly training load for the two athletes (#5 and #13) shown in Figure 2 and Table 1. An  
246 example traffic light system is shown for the month (incorporating the weekly load data)  
247 using the same traffic light thresholds discussed above. The differences between the two  
248 outputs are clearly visible.

249 Whether considering the data from a training prescription or injury prevention perspective,  
250 given the noted differences for each player, it is apparent that differentiated loading  
251 approaches should be prescribed for each. For example, Player #13 shows large variation in  
252 their monthly load – due in part to the high load obtained in week 1. In the example, this has  
253 resulted in a decision to reduce the exposure to load in week 2; therefore, the system provides  
254 a red flag. Together, these 2 weeks demonstrate inconsistency in loading, possibly increasing  
255 the risk of injury/illness. <sup>[42]</sup> In rectifying this, closer attention (in the context of this example)  
256 should be placed on the absolute and relative changes in load so as to prescribe more  
257 consistent loading. In contrast, Player #5 demonstrates relative consistency in their loading  
258 (range 1250 AU – 1850 AU). As such, a red flag (a change of ~300 load units) may not pose  
259 any meaningful risk to injury/illness. Collectively, this shows a number of complexities and  
260 factors to consider when individualising training prescription in team sports. The system

261 employed will thus require careful consideration of the relationships between each metric and  
262 those validity measures mentioned earlier in the article.

263

264

#### 265 **Step 4 – Communicating the findings**

266 Increasing the transparency in which data is displayed in scientific research has received  
267 considerable attention of late. <sup>[43]</sup> Figures which are able to display the response of the  
268 individual within the group have become more sophisticated as more advanced visualisation  
269 packages are available in commercial software. Figure 4 shows an example of how the same  
270 group means and standard deviations can be replicated using individual data, as well as how  
271 different tests of statistical significance change as a result of this differently distributed data.  
272 <sup>[43]</sup> This provides further support for visualisation of both the individual and group in order to  
273 understand the nature of the dataset. The great appeal of the traffic light approach is its ability  
274 to convey information visually in an intuitive and easily interpretable manner. The use of  
275 integrated plots, automated colour coding and conditional formatting, and visual flagging of  
276 outliers, anomalies and trends (both desirable and undesirable) provides regular feedback to  
277 the coach and support staff to guide daily decision making.

278

279 \*\*\* INSERT FIGURE 4 ABOUT HERE \*\*\*\*

#### 280 **The future**

281 Given the considerable human and financial investment in the pursuit of success, and the  
282 ethical importance of looking after individuals in our care, high performance sport will

283 continue to evolve in search of better ways to train and monitor athletes and to make  
284 decisions about how best to manage them to ensure both safety and success. The future will  
285 likely involve a mix of existing and new measurement approaches and technologies.  
286 However, to be most effective, and to provide a sound basis for decision support, all of the  
287 following will need to be developed and enhanced:

- 288 • Robust selection of athlete monitoring measures, with due consideration to issues  
289 related to validity, reliability, data reduction and athlete burden.
- 290 • Establishment of evidence-based guidelines related to the determination of  
291 benchmarks and baselines and the subsequent boundaries used for categories (e.g.,  
292 red, amber, green) within a decision support system.
- 293 • Development of database and dashboard software to enhance data management and  
294 visualisation.
- 295 • Application and exploration of analytic approaches to large datasets that account for  
296 longitudinal repeated measures data. Evaluation of multiple analysis approaches (i.e.,  
297 machine learning vs linear models) to the same datasets.
- 298 • Improved integration within multidisciplinary teams and the upskilling of staff and  
299 coaches in sport science and data analysis.
- 300 • The strategic implementation of research and innovation within high performance  
301 programmes, including rigorous data collection and question driven projects.
- 302 • The pursuit of research that encourages practitioners and researchers to answer  
303 questions through analysis of larger scale datasets facilitated through greater  
304 collaboration across clubs, leagues and sports.

305



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