Prevalence of interactions and influence of performance constraints on kick outcomes across Australian Football tiers: Implications for representative practice designs

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23   **Abstract**

24   **Introduction:** Representative learning design is a key feature of the theory of ecological dynamics,

25   conceptualising how task constraints can be manipulated in training designs to help athletes self-

26   regulate during their interactions with information-rich performance environments. Implementation of

27   analytical methodologies can support representative designs of practice environments by practitioners

28   recording how interacting constraints influence events, that emerge under performance conditions. To

29   determine key task constraints on kicking skill performance, the extent to which interactions of

30   constraints differ in prevalence and influence on kicking skills was investigated across competition

31   tiers in Australian Football (AF).

32   **Method:** A data sample of kicks (n = 29,153) was collected during junior, state-level and national

33   league matches. Key task constraints were recorded for each kick, with performance outcome

34   recorded as effective or ineffective. Rules were based on frequency and strength of associations

35   between constraints and kick outcomes, generated using the *Apriori* algorithm.

36   **Results:** Univariate analysis revealed that low kicking effectiveness was associated with physical

37   pressure (37%), whereas high efficiency emerged when kicking to an open target (70%). Between-

38   competition comparisons showed differences in constraint interactions through seven unique rules and

39   differences in confidence levels in shared rules.

40   **Discussion:** Results showed how understanding of key constraints interactions, and prevalence during

41   competitive performance, can be used to inform representative learning designs in athlete training

42   programmes. Findings can be used to specify how the competitive performance environment differs

43   between competition tiers, supporting the specification of information in training designs,

44   representative of different performance levels.

45

46   **Key words:** representative learning design, machine learning, Apriori algorithm, practice task design,

47   performance analysis, skill acquisition, kicking

48 **Introduction**

49   Representative learning design (RLD) is a key concept in the theoretical framework of

50 ecological dynamics that advocates the manipulation of task constraints in training. This approach to

51 training and practice in sport can shape continuous individual-environmental interactions to facilitate

52 the emergence of functional (relevant) decision-making and actions of athletes under competitive

53 performance conditions in sport [1-3]. Implementing RLD in training seeks to provide faithful

54 practice simulations of competitive environments to enhance performance [2]. When preparing

55 athletes for performance, the implementation of representative training designs requires a detailed,

56 evidence-based understanding of how key task constraints interact to influence behaviours [4]. The

57 level of task design fidelity can be informed through recorded data on the prevalence and interaction

58 of constraints in a competitive performance environment [5, 6]. It has been argued that analysis and

59 comprehension of the nature of constraints in performance settings is a key role for coaches in

60 practice design [7].

61   Currently, events and outcomes are captured in statistical analysis of team sports performance.

62 This typically occurs through player trajectory analysis and frequency count data recording

63 performance variables including kicks, tackles and fouls, without accounting for the context in which

64 they emerge [8]. Determining the influential constraints within competitive performance, with respect

65 to their impact on key performance outcomes, would provide an evidence-based approach to practice

66 designs, harnessing the power of performance analysis and evaluations [5, 9]. When constraints are

67 used for this purpose, they tend to be viewed in a univariate manner, with respect to match context.

68 For example, score margin and kick location [10, 11], playing at home or away [12], or dynamic

69 game conditions [13] are used to discern various aspects of performance. However, it has been

70 proposed that multiple constraints *interact* to influence (a) team sports performer(s) concomitantly

71 during skilled activities [14]. Thus, a constraints-led perspective on performance analysis can

72 facilitate the creation of a more effective and efficient representative design in practice. This is due to

73 highlighting the importance of the greater team sports performance system and how it is a

74 combination of interacting sub-systems [6]. By evaluating a performance outcome with respect to

interacting constraints, the context surrounding competitive performance can be considered, providing an objective, evidence-based assessment of performance.

A recent study illustrated a methodology to identify the most commonly occurring constraint interactions experienced in field kicking in the AFL, through utilising a machine learning algorithm.[5] The higher the number of constraints in a model, the greater the associated level of understanding of performance outcomes [5, 6, 15]. However, the feasibility of including all constraints and contextual variables in a performance analysis model is often low in an applied practice setting, given the exponential number of interactions which may exist between key performance variables [5]. The application of machine learning may identify *meaningful interactions of constraints* in competition which may then be reproduced in representative designs of practice. Critically, this process is not feasible through human observation or the application of traditional linear statistical techniques due to limitations of both [5].

Australian Football (AF) is an invasion-style sport played on an oval with 22 players per side, 18 on the field and 4 on the interchange [16]. Due to the large playing area and number of players involved, an understanding of key constraints which shape scoring opportunities is crucial. Kicking is an important action in AF, as it constitutes the predominant form of strategic ball movement and the sole manner in which a goal can be scored. On average, each player executes a kick every ten minutes within an AFL match [17].

Further, AF is a dynamic sport at all skill levels, with an unpredictable nature due to a large number of varying factors that impinge on performance [18]. The completion of a successful kick is a resultant of multiple attributes of the game and the immediate constraints that emerge on the kick, such as opposition pressure, team mates' availability and the current status of the ball carrier him/herself [18]. Despite this key performance feature, little is known about the interaction of key task constraints placed on these kicks and how these differ across competition tiers. Information on significant performance constraints at different levels of structured competition would facilitate the implementation of task constraints to improve kicking performance in training and games [19].

Key performance differences have been described between elite, sub-elite and underage athletes across a number of sports. Running distances and high intensity movements differ by age and are greater in elite, compared to high-level female soccer players [20, 21]. Within volleyball, performance indicators, physical and physiological outputs differ between elite and sub-elite athletes [22]. Yet, no research has been conducted on how constraint interactions can differ on performances

106 between competition tiers. It is possible that constraints interactions may change as a function of

107 competition tier. Whilst the data reported by Robertson, Spencer [5] describe constraints interactions

108 within the senior AFL competition, the same manipulations may not provide a RLD for practice in

109 other tiers of AF competition (e.g., junior and club levels). An understanding of the demands of

110 specific competitive performance environments is vital to produce representative designs which align

111 with specific levels of competition.

112   This study aimed to ascertain where there are differences in the influence and prevalence of

113 constraints which exist between competitive performance at: (i) U18 years of age (U18) competitions,

114 (ii) senior state leagues, and (iii), the professional AF League. Further, it attempts to evaluate how the

115 efficacy of exploring effects of numerous interacting constraints can provide a more inclusive

116 measure of constraint influence on field kicking, compared to uni- and bi-variate approaches.

117

118 **Methodology**

119 Data were collected across underage, sub-elite and elite Australian Football competitions from the

120 2016, 2017 and 2018 seasons (Table 1). Approval to conduct the study was obtained by the University

121 Human Research Ethics Committee. A code window was developed in SportsCode (10.3.14, Hudl,

122 Lincoln, Nebraska, United States of America) to record six constraints on field kicking performance,

123 represented as a binary 'effective' or 'ineffective' kick using video footage. A kick was determined

124 to be 'effective' or 'ineffective' based on a range of potentially impinging factors such as kick intent,

125 kick position, number of defenders located near the kicker and kick distance *as defined by Champion*

126 *Data the official statistics provider of the Australian Football League.*

127 This was subject to human interpretation. These constraints are shown in Figure 1. For example,

128 pressure was coded as a four-level constraint, based on the action and direction of the opposing

129 defender. These were: closing, chasing, physical or no pressure. The constraints categories and levels

130 implemented in this study were based *on Champion Data's codes where possible, otherwise they*

131 *were based upon previous research by Back [23], Robertson, Spencer [5], Ireland, Dawson [24], as*

132 *well as* consultations with two experienced coaches from a professional AFL team.

133 A total of 29,153 kicks were coded.

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139   Descriptive statistics (means, standard deviations and 95% confidence intervals, CIs) relating

140 to kick effectiveness were calculated and reported for each individual constraint type. Descriptive

141 statistics relating to kick effectiveness, shaped by pairs of interacting constraint types, time in

142 possession-distance and time in possession-pressure, were obtained.

143   To determine both the prevalence and influence of constraint interactions on kick outcomes, a

144 rule induction approach was utilised. Rule induction is a branch of machine learning, which is capable

145 of identifying underlying and frequent patterns between variables in a large transactional database [5,

146 25]. Specifically, the '*Arules*' package [26] was used to run the *Apriori* algorithm. The model was set

147 to only produce rules which incorporated five categories of constraint and contained the performance

148 outcome (effective or ineffective) as the resultant. As identified, a benefit of association rules is the

149 ability to find patterns which are typically less identifiable through observation by the human eye

150 [27]. A minimum support value of 0.0005 was selected for both models in order to generate a

151 minimum of five rules which met the set criteria.

152   Data were grouped based on level of competition by U18 (kicks n = 16,963), State level

153 leagues (kicks n = 3,185) and the AFL (kicks n = 9,005), as outlined in Table 1. Models were then

154 built for each competition tier using the same criteria outlined above. To compare the rules generated

155 between tiers, the number of unique and duplicated rules were compared alongside their variation in

156 confidence levels [28].

157

158 **Results**

159 The average match kicking effectiveness value, regardless of which constraints were present, was

160 54%. The overall mean effectiveness values for each level of the six constraints are shown in Figure

161 2. Kicking to an open target resulted in an effective kick 70% of the time, while kicking under

162 physical pressure resulted in the lowest (37%) of kicking effectiveness. Time in possession of 0 to 2

163 seconds demonstrated a level of 50% effectiveness, whilst time in possession for between 4 to 6

164 seconds was effective 64% of the time. Possession source, or how the ball was gained, had a clear

165 influence on kick effectiveness with three levels of constraint, ground ball, handball received and

166 stoppage, all representing unstructured and general play, falling below average effectiveness and two

167 types of possession source above average. In contrast, the two constraint levels above average kick

168 effectiveness, sourcing the ball from either a mark or free kick, both represent set plays.

169

170 **** INSERT FIGURE 2 HERE ****

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173 As an example of bivariate constraint interaction, how time in possession can interact with

174 pressure is displayed in Figure 3. Kick effectiveness is altered by the relationship between pressure

175 and time in possession. A kick under physical pressure from an immediate opponent ranges in

176 effectiveness from 37% to 71%, depending on the level of time afforded to the performer. Under

177 frontal pressure, this varies from 43% to 56%, based on the time in possession. The relationship

178 between kick distance and time also shows a range, with differences between kicks <40 metres long

179 displaying increased effectiveness with longer time in possession: for 4 to 6 secs or > 6 secs. Kicks

180 over 40 metres have increased effectiveness with shorter time in possession: 0 to 2 secs and 2 to 4

181 secs (Figure 3).

182

183 **** INSERT FIGURE 3 HERE ****

184

185 The rule induction approach resulted in 22 rules, which influenced kick effectiveness, with

186 confidence results ranging from 43% to 87%. Fifteen rules had an influence on kick ineffectiveness,

187 with confidence results ranging from 13% to 85%. Only the top five rules for an effective and

188 ineffective kick were analysed (see Figure 4).

189

190   **** INSERT FIGURE 4 HERE ****

191

192   A comparison between U18, state leagues and the national competition athletes was

193   conducted, with the 10 strongest rules based on confidence for each tier outlined in Figure 5.

194

195   **** INSERT FIGURE 5 HERE ****

196   **** INSERT FIGURE 6 HERE ****

197

198   **Discussion**

199   This study demonstrated how constraint interactions influenced kicking performance, across three

200   performance tiers of AF competitions. Further, the importance of accounting for constraint

201   interaction, as constraints interacted with one another which altered performance outcomes. In

202   research, the interaction of constraints on field kicking has only been examined at the professional tier

203   [5]. However, results from the AFL competition only are not representative of other performance

204   tiers. Results demonstrated differences between performance tiers which may enable more specific

205   representative designs in athlete preparation and development, to inform training practices and player

206   evaluation at different performance levels.

207   Analysis of task constraints in a univariate manner can be misleading, as constraints exist

208   concomitantly and are continually impacting on each other [29]. This study demonstrated the large

209   influence that an individual constraint can have on kick effectiveness. This is illustrated by the

210   considerable difference between the highest and lowest kicking effectiveness between kicking to an

211   open player, who is under no immediate pressure from the opposition (70%), or kicking under

212   physical pressure (37%). The bivariate analysis (see Figure 3) demonstrated how the addition of even

213   a single constraint can influence performance outcome to a great extent. Further, Figure 3b

214   demonstrates that a constraint such as *time* has a 'sweet-spot', meaning that having ball possession for

215   a short or long period of time may not necessarily be advantageous for a performer. Maintaining

216   possession for between 2 to 4 or 4 to 6 secs for kicks under or over 40 metres respectively, may result

217 in the emergence of a higher percentage of effective kicks. However, the addition of further task

218 constraints, which further simulate performance conditions, may offer greater insights into how

219 constraints interactions influence performance.

220 As identified, the inclusion of additional constraints offers a unique story to the isolated univariate

221 and bivariate approaches. Incorporating conditional constraints interactions in test design could

222 improve the level of task representativeness [30]. To illustrate the need to account for constraint

223 interaction the ranking of 0 to 2 secs for time in possession will be used. The univariate analysis

224 showed 0 to 2 secs results in an average effectiveness of 50% on kicking performance, only 4% below

225 average. Without the rule induction approach, in which time in possession of 0 to 2 secs is present in

226 the five ineffective kick rules, the potential importance of this constraint may have been overlooked.

227 Figure 6 demonstrates how the tallying of additional constraints exhibits that, as more constraint

228 variables are added in performance modelling, a more comprehensive insight into the influence of

229 constraint interactions can be gained. This finding illustrates how comparing an athlete's performance

230 to average kick effectiveness does not provide a fair comparison on which to judge an individual's

231 performance.

232 Understanding the nature of competitive performance constraints could also support an

233 objective consideration of player evaluation and assessment. Representative performance tests would

234 enable coaches to objectively view kick difficulty and support a fairer assessment of player

235 performance output through the incorporation of context in task design [31]. For instance, if a player

236 had three kicks during a game and only one was effective, their kicking efficiency would be rated at

237 33% and well below average, without any context provided. However, coaches need to consider the

238 constraints placed on the individual kicks to ascertain whether all three kicks resulted from winning

239 the ball from a stoppage, with the performer being under pressure and in possession of the ball for less

240 than two secs, whilst making a short kick. Under these performance constraints an average value of

241 expected kicking effectiveness would be 14.6% (Figure 4), offering a very different perspective on

242 player performance.

243 Constraints interaction was measured with the rule induction approach which included five

244 constraints, advancing the specification of rules in the study by Robertson, Spencer [5], who included

245   only three constraints. Despite these small methodological differences, the findings align with data

246   observed within the elite AF competition level [5]. Confidence levels in effective kicks in both studies

247   are within the 80-90% range and suggest that players perform better when kicking over shorter

248   distances to an open target (e.g., an unmarked teammate or space on-field). Similar to findings

249   reported by Robertson, Spencer [5], the top five rules for effective kicks, are conducted under no

250   pressure, from a kick < 40 metres and a majority from either a mark or a free kick. Within AF

251   competitions, a mark and free kick are the only circumstances where possession can be taken without

252   physical pressure being applied by the opposition. Conversely, for ineffective kicks, similar rules had

253   a greater range in their confidence levels, ranging from 15% to 39% compared to the range of 38 to

254   45% in Robertson, Spencer [5]. This study revealed that the most common circumstances whereby an

255   ineffective kick emerged was from possession sources related to open play situations. This

256   observation combined with the short time in possession for ineffective kicks, could lead to speculation

257   that players potentially do not have the skillset to gather or receive the ball under severe time

258   constraints to kick effectively to a covered target (e.g., marked teammate or space). The differences

259   between the findings of this study and other investigations of performance in AF may be due to a

260   range of factors such as skill level, decision-making abilities, age and experience of the participant

261   sample studied [32-34].

262   Understanding differences between tiers is crucial for creating a training design which is

263   representative of the tier. Analysis of performance between tiers resulted in seven unique rules, four

264   rules shared between two tiers and five rules found across all tiers (Figure 5). Of all ten AFL rules

265   identified by our methods, seven were found to be operative in either the state leagues or the U18 tier.

266   Two of the three unique rules found in the AFL, included a kick target of a covered or leading player,

267   which was found in only four rules produced by all three tiers. Kicking to a covered or leading target

268   could be a more difficult kick to execute and, thus, it is somewhat unsurprising that they are found in

269   two rules unique to the elite AFL competition. Between the U18 and state leagues tiers, greater

270   variation exists in the nature of the seven shared rules. The state leagues were ranked more highly in

271   four rules based on levels of confidence (Figure 5). Three rules contained constraints which come

272   from an open play style of possession source (i.e., handball receive or groundball). Although

273   conjecture, often in match conditions, these possession types have more pressure as they take place in

274   dynamic, open play situations. The present findings are similar to those reported in other sports,

275   where athletes from higher performance levels display improved skill performance outcomes

276   compared to lower tiers [22]. The ability to cope in these situations may be due to individual factors,

277   including the age, learning, development and greater practice and performance experiences of these

278   more skilled individuals [35]. Incorporating individual constraints may also aid in understanding

279   differences and development between sub-elite and elite players.

280   Understanding how athletes maintain their skill level under competitive performance conditions,

281   and how this differs across performance tiers is essential knowledge for sports practitioners seeking to

282   enhance the effectiveness and efficiency of training designs and transfer between practice and

283   competition [2, 5, 11]. Accounting for different performance tiers facilitates the adoption of targeted

284   and representative training designs for athlete preparation, aligned with their developmental status, as

285   opposed to attempting to use generic training designs which may be more suitable for athletes in other

286   competitive performance tiers. As demonstrated in Figure 5 and as observed in differences with data

287   reported by Robertson, Spencer [5], the importance for accounting for influence of performance tier is

288   vital to designing representative training environments. Differences in skilled performance exist at

289   different tiers, potentially due to the changing prevalence and interaction of constraints. Thus, data

290   obtained on performance from one tier cannot be transferred to the design of practice tasks for athletes

291   in another competitive level due to specificity and representativeness of training designs. This

292   observation emphasises the importance of understanding the specific athlete-environment interactions

293   that occur in competitive performance conditions to develop a representative training designs [2].

294   A rule based approach may provide an objective tool to help quantify the level of

295   representativeness within a practice task design which can complement existing subjective

296   approaches, which rely on experiential knowledge of elite sport practitioners [5, 11, 36]. This could

297   improve the effectiveness and efficiency of designing training tasks which replicate competition

298   environments, allowing them to target specific strengths and weaknesses within training, based on

299   competition tier [2, 5]. This information could be used by coaches in multiple ways. First, they could

300   seek to incorporate a constraints-led approach into their training design to create more challenging

301 and realistic practice task designs where athletes are faced with these competition-environment

302 constraints [2]. Alternatively, this type of design may afford opportunities for performers to

303 experience a strategic effect on decision-making processes.

304 Given the increasing availability of larger datasets there is scope for future research to develop

305 both team and individual-specific performance models to facilitate specificity of training designs. The

306 power of these models could be enhanced by adding further constraints and contextual variables, such

307 as such as physical output, field location and score margin of kicks to improve the predicted outcomes

308 of skilled actions, and the representativeness of training designs [32, 37]. Feasibility of incorporating

309 a large number of contextual variables and constraints into performance analysis can be limited due to

310 challenges of interpreting large volumes of data in a time effective manner [38]. Large datasets can

311 impose some feasibility issues around data management. In the current study 5,060 (17%) kicks were

312 missing a measurement for at least one of the seven constraints. Further, differences in sample sizes

313 of kicks collected at each performance tier meant that some rules found in the smaller dataset had the

314 potential to be more prevalent due to a bias from the competitive games analysed. Additionally, due to

315 the manual treatment of discrete constraints, some constraints contained just two levels (i.e., kick

316 distance) and others five (i.e., possession source), a potential for bias in rule frequencies exists due to

317 the number of options within a specific constraint. Future research could use a continuous scale or

318 fuzzy approaches to help account for this potential bias [39]. Automated capture of data through deep

319 learning and computer vision may aid in reducing time required and alleviate issues around manual

320 data collection and interpretation [5, 38].

321

322 **Conclusion**

323 This study compared the variations in constraint interactions upon kicking action outcomes in AF

324 across three different performance tiers. When effects of constraints are viewed in isolation, or pairs,

325 they can offer some insight into what a player is experiencing in specific performance contexts.

326 However, when all (or many) constraints are considered, a more complete picture can be provided.

327 Rule induction provides a method capable of determining high frequency events and their outcomes.

328 Findings from this analytics approach in research can be used to assess kicking performance of

329   players, providing greater performance context to aid interpretation by practitioners. This information

330   may then be used for player selection and recruitment purposes. The methodologies presented are not

331   limited to kicking constraints, as sport specific constraints can be used to gain further understanding

332   of performance conditions across a range of team sports. This analytics methodology may better

333   inform and objectively define key events competitive performance which can be simulated in training,

334   and make using a RLD framework more effective and efficient. Whilst there are specificities in

335   differences between rules of AF and other team sports, the current findings cannot be transferred to

336   other sports. However, the analytic methods presented here can be. Understanding how the interaction

337   of constraints differs across performance tiers is vital to creating a representative design specific for

338   player assessment and practice task composition for specific competitive performance tiers.

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References

1. Davids, K., C. Button, and S. Bennet, *Dynamics of skill acquisition: a constraints-led approach*. 2008: Human Kinetics.
2. Pinder, R., et al., *Representative learning design and functionality of research and practice in sport.* Journal of Sport and Exercise Psychology, 2011. **33**(1): p. 146-155.
3. Mccosker, C., et al., *How performance analysis of elite long jumping can inform representative training design through identification of key constraints on competitive behaviours.* European journal of sport science, 2019: p. 1-9.
4. Renshaw, I., et al., *The Constraints-Led Approach: Principles for Sports Coaching and Practice Design*. 1st ed. Routledge Studies in COnstraints-Based Methodologies in Sport. 2019, London: Routledge.
5. Robertson, S., et al., *A rule induction framework for the determination of representative learning design in skilled performance.* Journal of Sport Science, 2019.
6. Davids, K., et al., *Movement models from sports provide representative task constraints for studying adaptive behavior in human movement systems.* Adaptive behavior, 2006. **14**(1): p. 73-95.
7. Araújo, D., et al., *Emergence of sport skills under constraints*, in *Skill acquisition in sport: Research, theory and practice*, A.M. Williams and N.J. Hodges, Editors. 2004, Routledge. p. 409.
8. Gudmundsson, J. and M. Horton, *Spatio-Temporal Analysis of Team Sports - A Survey.* arXiv 1602.06994, 2016.
9. Farrow, D. and S. Robertson, *Development of a skill acquisition periodisation framework for high-performance sport.* Sports Medicine, 2017. **47**(6): p. 1043-1054.
10. Reich, B.J., et al., *A spatial analysis of basketball shot chart data.* The American Statistician, 2006. **60**(1): p. 3-12.
11. Pocock, C., et al., *Hot hands, cold feet? Investigating effects of interacting constraints on place kicking performance at the 2015 Rugby Union World Cup.* European journal of sport science, 2018: p. 1-8.
12. Goldman, M. and J.M. Rao. *Effort vs. concentration: the asymmetric impact of pressure on NBA performance*. in *Proceedings of the mit sloan sports analytics conference*. 2012.
13. Farrow, D. and M. Reid, *The effect of equipment scaling on the skill acquisition of beginning tennis players.* Journal of Sports Sciences, 2010. **28**(7): p. 723-732.
14. Araújo, D. and K. Davids, *The (Sport) Performer-Environment System as the Base Unit in Explanations of Expert Performance.* Journal of Expertise/December, 2018. **1**(3).
15. Araújo, D. and K. Davids, *Team synergies in sport: theory and measures.* Frontiers in psychology, 2016. **7**: p. 1449.
16. Gray, A.J. and D.G. Jenkins, *Match analysis and the physiological demands of Australian football.* Sports Medicine, 2010. **40**(4): p. 347-360.
17. Johnston, R., et al., *Movement demands and match performance in professional Australian football.* International journal of sports medicine, 2012. **33**(02): p. 89-93.
18. Pill, S., *Informing game sense pedagogy with constraints led theory for coaching in Australian football.* Sports Coaching Review, 2014. **3**(1): p. 46-62.
19. Farrow, D., *Challenging traditional practice approaches to AFL kicking skill development*. 2010, Victoria University School of Sport and Exercise and the Australian Institute of Sport.

390 20. Mohr, M., et al., *Match activities of elite women soccer players at different
391   performance levels.* The Journal of Strength & Conditioning Research, 2008. **22**(2): p.
392   341-349.
393 21. Buchheit, M., et al., *Match running performance and fitness in youth soccer.*
394   International journal of sports medicine, 2010. **31**(11): p. 818-825.
395 22. Smith, D., D. Roberts, and B. Watson, *Physical, physiological and performance
396   differences between Canadian national team and universiade volleyball players.*
397   Journal of Sports Sciences, 1992. **10**(2): p. 131-138.
398 23. Back, N., *The influence of constraints on athlete kicking performance in training and
399   matches at an elite Australian Rules football club*, in *Institute of Sport, Exercise and
400   Active Living.* 2015, Victoria University.
401 24. Ireland, D., et al., *Do we train how we play? Investigating skill patterns in Australian
402   football.* Science and Medicine in Football, 2019: p. 1-10.
403 25. Agarwal, R. and R. Srikant. *Fast algorithms for mining association rules*. in *Proc. of
404   the 20th VLDB Conference*. 1994.
405 26. Hahsler, M., et al., *Package 'arules'.* 2018.
406 27. Morgan, S. *Detecting Spatial Trends in Hockey Using Frequent Item Sets*. in
407   *Proceedings of the 8th International Symposium on Computer Science in Sport*. 2011.
408 28. Dudek, D. *Measures for Comparing Association Rule Sets*. in *International Conference
409   on Artificial Intelligence and Soft Computing*. 2010. Berlin, Heidelberg: Springer
410   Berlin Heidelberg.
411 29. Newell, K.M., *Constraints on the development of coordination.* Motor development
412   in children: Aspects of coordination and control, 1986. **34**: p. 341-360.
413 30. Vilar, L., et al., *The need for 'representative task design'in evaluating efficacy of skills
414   tests in sport: A comment on Russell, Benton and Kingsley (2010).* Journal of sports
415   sciences, 2012. **30**(16): p. 1727-1730.
416 31. Quarrie, K.L. and W.G. Hopkins, *Evaluation of goal kicking performance in
417   international rugby union matches.* Journal of science and medicine in sport, 2015.
418   **18**(2): p. 195-198.
419 32. Royal, K.A., et al., *The effects of fatigue on decision making and shooting skill
420   performance in water polo players.* Journal of Sports Sciences, 2006. **24**(8): p. 807-
421   815.
422 33. Abernethy, B., *The effects of age and expertise upon perceptual skill development in
423   a racquet sport.* Research quarterly for exercise and sport, 1988. **59**(3): p. 210-221.
424 34. Williams, A.M., *Perceptual skill in soccer: Implications for talent identification and
425   development.* Journal of sports sciences, 2000. **18**(9): p. 737-750.
426 35. Renshaw, I., et al., *A constraints-led perspective to understanding skill acquisition
427   and game play: A basis for integration of motor learning theory and physical
428   education praxis?* Physical Education and Sport Pedagogy, 2010. **15**(2): p. 117-137.
429 36. Krause, L., et al., *Helping coaches apply the principles of representative learning
430   design: validation of a tennis specific practice assessment tool.* Journal of sports
431   sciences, 2018. **36**(11): p. 1277-1286.
432 37. Ávila-Moreno, F.M., et al., *Evaluation of tactical performance in invasion team
433   sports: a systematic review.* International Journal of Performance Analysis in Sport,
434   2018: p. 1-22.

435   38.   Couceiro, M.S., et al., *The ARCANE project: how an ecological dynamics framework*
436   *can enhance performance assessment and prediction in football.* Sports Medicine,
437   2016. **46**(12): p. 1781-1786.
438   39.   Cariñena, P., *Fuzzy temporal association rules: combining temporal and quantitative*
439   *data to increase rule expressiveness.* Wiley Interdisciplinary Reviews: Data Mining
440   and Knowledge Discovery, 2014. **4**(1): p. 64-70.
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443   Table 1. Breakdown of total kicks per league and tier.

Competition	Tier	Number of kicks
Academy Series	U18 Competition	701
Australian Football League Academy	U18 Competition	170
Australian Football League	AFL	9,005
Australian Underage Championships	U18 Competition	1,890
North East Australian Football League	State league	809
South Australian National Football League	State league	491
South Australian National Football League (Reserves)	State league	657
South Australian National Football League (Under 18)	U18 Competition	998
School Football	U18 Competition	37
TAC Cup	U18 Competition	11,625
Victorian Football League	State league	934
Western Australian Football League	State league	266
Western Australian Football League (Reserves)	State league	28
Western Australian Football League (Under 18)	U18 Competition	1,542
TOTAL		**29,153**

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