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

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

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Abstract

Introduction: Representative learning design is a key feature of the theory of ecological dynamics, conceptualising how task constraints can be manipulated in training designs to help athletes self-regulate during their interactions with information-rich performance environments. Implementation of analytical methodologies can support representative designs of practice environments by practitioners recording how interacting constraints influence events, that emerge under performance conditions. To determine key task constraints on kicking skill performance, the extent to which interactions of constraints differ in prevalence and influence on kicking skills was investigated across competition tiers in Australian Football (AF).

Method: A data sample of kicks (n = 29,153) was collected during junior, state-level and national league matches. Key task constraints were recorded for each kick, with performance outcome recorded as effective or ineffective. Rules were based on frequency and strength of associations between constraints and kick outcomes, generated using the *Apriori* algorithm.

Results: Univariate analysis revealed that low kicking effectiveness was associated with physical pressure (37%), whereas high efficiency emerged when kicking to an open target (70%). Between-competition comparisons showed differences in constraint interactions through seven unique rules and differences in confidence levels in shared rules.

Discussion: Results showed how understanding of key constraints interactions, and prevalence during competitive performance, can be used to inform representative learning designs in athlete training programmes. Findings can be used to specify how the competitive performance environment differs between competition tiers, supporting the specification of information in training designs, representative of different performance levels.

Key words: representative learning design, machine learning, Apriori algorithm, practice task design, performance analysis, skill acquisition

Introduction

Representative learning design (RLD) is a key concept in the theoretical framework of ecological dynamics that advocates the manipulation of task constraints in training. This approach to training and practice in sport can shape continuous individual-environmental interactions to facilitate the emergence of functional (relevant) decision-making and actions of athletes under competitive performance conditions in sport (Davids, Button, & Bennet, 2008; Mccosker, Renshaw, Greenwood, Davids, & Gosden, 2019; Pinder, Davids, Renshaw, & Araújo, 2011). Implementing RLD in training seeks to provide faithful practice simulations of competitive environments to enhance performance (Pinder, et al., 2011). When preparing athletes for performance, the implementation of representative training designs requires a detailed, evidence-based understanding of how key task constraints interact to influence behaviours (Renshaw, Davids, Newcombe, & Roberts, 2019). This can be informed through recorded data on the prevalence and interaction of constraints in a competitive performance environment (Davids, Button, Araújo, Renshaw, & Hristovski, 2006; Robertson, Spencer, Back, & Farrow, 2018). It has been argued that analysis and comprehension of the nature of constraints in performance settings is a key role for coaches in practice design (Araújo, Davids, Bennett, Button, & Chapman, 2004).

Currently, events and outcomes are captured in statistical analysis of team sports performance. This typically occurs through player trajectory analysis and frequency count data recording performance variables including kicks, tackles and fouls, without accounting for the context in which they emerge (Gudmundsson & Horton, 2016). Determining the influential constraints within competitive performance, with respect to their impact on key performance outcomes, would provide an evidence-based approach to practice designs, harnessing the power of performance analysis and evaluations (Farrow & Robertson, 2017; Robertson, et al., 2018). When constraints are used for this purpose, they tend to be viewed in a univariate manner, with respect to match context. For example, score margin and kick location (Pocock, Bezodis, Davids, & North, 2018; Reich, Hodges, Carlin, & Reich, 2006), playing at home or away (Goldman & Rao, 2012), or dynamic game conditions (Farrow & Reid, 2010) are used to discern various aspects of performance. However, multiple constraints interact to influence (a) team sports performer(s) concomitantly during skilled activities (Araújo &

Davids, 2018). Thus, a constraints-led perspective on performance analysis can facilitate the creation of a more effective and efficient representative design in practice. This is due to highlighting the importance of the greater team sports performance system and how it is a combination of interacting sub-systems (Davids, et al., 2006). 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.(Robertson, et al., 2018) The higher the number of constraints in a model, the greater the associated level of understanding of performance outcomes (Davids, et al., 2006; Robertson, et al., 2018). 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 (Robertson, et al., 2018). 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 in both (Robertson, et al., 2018).

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 (Gray & Jenkins, 2010). 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 (Johnston, et al., 2012). Despite this key performance feature, little is known about how the key task constraints placed on these kicks interact to shape behaviours and how these differ across competition tiers.

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 (Buchheit, Mendez-Villanueva, Simpson, & Bourdon, 2010; Mohr, Krustrup, Andersson, Kirkendal, & Bangsbo, 2008). Within volleyball, performance indicators, physical and physiological outputs differ between elite and sub-elite athletes (Smith, Roberts, & Watson, 1992). Yet, no research has been conducted on how constraint interactions can differ on performances between competition tiers. It is possible that constraints interactions may change as a function of competition tier. Whilst the data reported by Robertson, et al. (2018) describe constraints interactions within the senior AFL competition, the same manipulations may not provide a RLD for practice in other tiers of AF competition (e.g., junior and club levels). An understanding of the demands of specific competitive performance environments is vital to produce representative designs which align with specific levels of competition.

This study aimed to ascertain where there are differences in the influence and prevalence of constraints which exist between competitive performance at: (i) U18 years of age (U18) competitions, (ii) senior state leagues, and (iii), the professional AF League. Further, it attempts to evaluate how the efficacy of exploring effects of numerous interacting constraints can provide a more inclusive measure of constraint influence on field kicking, compared to uni- and bi-variate approaches.

Methodology

Data were collected across underage, sub-elite and elite Australian Football competitions from the 2016, 2017 and 2018 seasons (Table 1). Approval to conduct the study was obtained by the University Human Research Ethics Committee. A code window was developed in SportsCode (10.3.14, Hudl, Lincoln, Nebraska, United States of America) to record six constraints on field kicking performance, represented as a binary 'effective' or 'ineffective' kick using video footage. A kick was determined to be 'effective' or 'ineffective' based on a range of factors such as kick intent, kick position, number of defenders and distance. This was subject to human interpterion. These constraints are shown in Figure 1. For example, pressure was coded as a four-level constraint, based on the action and direction of the opposing defender. These were: closing, chasing, physical or no pressure. The constraints categories and levels used were based upon on their applicability to the field and consultations with two coaches from an AFL team (Robertson, et al., 2018). A total of 29,153 kicks were coded.

**** INSERT TABLE 1 HERE ****

****INSERT FIGURE 1 HERE ****

Descriptive statistics (means, standard deviations and 95% confidence intervals, CIs) relating to kick effectiveness were calculated and reported for each individual constraint type. Descriptive statistics relating to kick effectiveness, shaped by pairs of interacting constraint types, time in possession-distance and time in possession-pressure, were obtained.

To determine both the prevalence and influence of constraint interactions on kick outcomes, a rule induction approach was utilised. Rule induction is a branch of machine learning, which is capable of identifying underlying and frequent patterns between variables in a large transactional database (Agarwal & Srikant, 1994; Robertson, et al., 2018). Specifically, the '*Arules*' package (Hahsler, Buchta, Gruen, & Hornik, 2018) was used to run the *Apriori* algorithm. The model was set to only produce rules which incorporated five categories of constraint and contained the performance outcome (effective or ineffective) as the resultant. As identified, a benefit of association rules is the ability to find patterns which are typically less identifiable through observation by the human eye (Morgan, 2011). A minimum support value of 0.0005 was selected for both models in order to generate a minimum of five rules which met the set criteria.

Data were grouped based on level of competition by U18 (kicks n = 16,963), State level leagues (kicks n = 3,185) and the AFL (kicks n = 9,005), as outlined in Table 1. Models were then built for each competition tier using the same criteria outlined above. To compare the rules generated between tiers, the number of unique and duplicated rules were compared alongside their variation in confidence levels (Dudek, 2010).

Results

The average match kicking effectiveness value, regardless of which constraints were present, was 54%. The overall mean effectiveness values for each level of the six constraints are shown in Figure 2. Kicking to an open target resulted in an effective kick 70% of the time, while kicking under physical pressure resulted in the lowest (37%) of kicking effectiveness. Time in possession of 0 to 2 seconds demonstrated a level of 50% effectiveness, whilst time in possession for between 4 to 6 seconds was effective 64% of the time. Possession source, or how the ball was gained, had a clear influence on kick effectiveness with three levels of constraint, ground ball, handball received and stoppage, all representing unstructured and general play, falling below average effectiveness and two types of possession source above average. In contrast, the two constraint levels above average kick effectiveness, sourcing the ball from either a mark or free kick, both represent set plays.

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

As an example of bivariate constraint interaction, how time in possession can interact with pressure is displayed in Figure 3. Kick effectiveness is altered by the relationship between pressure and time in possession. A kick under physical pressure from an immediate opponent ranges in effectiveness from 37% to 71%, depending on the level of time afforded to the performer. Under frontal pressure, this varies from 43% to 56%, based on the time in possession. The relationship between kick distance and time also shows a range, with differences between kicks <40 metres long displaying increased effectiveness with longer time in possession: for 4 to 6 secs or > 6 secs. Kicks over 40 metres have increased effectiveness with shorter time in possession: 0 to 2 secs and 2 to 4 secs (Figure 3).

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

The rule induction approach resulted in 22 rules, which influenced kick effectiveness, with confidence results ranging from 43% to 87%. Fifteen rules had an influence on kick ineffectiveness, with confidence results ranging from 13% to 85%. Only the top five rules for an effective and ineffective kick were analysed (see Figure 4).

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

A comparison between U18, state leagues and the national competition athletes was conducted, with the 10 strongest rules based on confidence for each tier outlined in Figure 5.

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

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

Discussion

This study demonstrated how constraint interactions influenced kicking performance, across three performance tiers of AF competitions. Further, the importance of accounting for constraint interaction, as constraints interacted with one another which altered performance outcomes. In research, the interaction of constraints on field kicking has only been examined at the professional tier (Robertson, et al., 2018). However, results from the AFL competition only are not representative of other performance tiers. Results demonstrated differences between performance tiers which may enable more specific representative designs in athlete preparation and development, to inform training practices and player evaluation at different performance levels.

Analysis of task constraints in a univariate manner can be misleading, as constraints exist concomitantly and are continually impacting on each other (Newell, 1986). This study demonstrated the large influence that an individual constraint can have on kick effectiveness. This is illustrated by the considerable difference between the highest and lowest kicking effectiveness between kicking to an open player, who is under no immediate pressure from the opposition (70%), or kicking under physical pressure (37%). The bivariate analysis (see Figure 3) demonstrated how the addition of even a single constraint can influence performance outcome to a great extent. Further, Figure 3b demonstrates that a constraint such as *time* has a 'sweet-spot', meaning that having ball possession for a short or long period of time may not necessarily be advantageous for a performer. Maintaining possession for between 2 to 4 or 4 to 6 secs for kicks under or over 40 metres respectively, may result in the emergence of a higher percentage of effective kicks. However, the addition of further task constraints, which further simulate performance conditions, may offer greater insights into how constraints interactions influence performance.

As identified, the inclusion of additional constraints offers a unique story to the isolated univariate and bivariate approaches. Incorporating conditional constraints interactions in test design could improve the level of task representativeness (Vilar, Araújo, Davids, & Renshaw, 2012). To illustrate the need to account for constraint interaction the ranking of 0 to 2 secs for time in possession will be used. The univariate analysis showed 0 to 2 secs results in an average effectiveness of 50% on kicking performance, only 4% below average. Without the rule induction approach, in which time in possession of 0 to 2 secs is present in the five ineffective kick rules, the potential importance of this constraint may have been overlooked. Figure 6 demonstrates how the tallying of additional constraints exhibits that, as more constraint variables are added in performance modelling, a more comprehensive insight into the influence of constraint interactions can be gained. This finding illustrates how comparing an athlete's performance to average kick effectiveness does not provide a fair comparison on which to judge an individual's performance.

Understanding the nature of competitive performance constraints could also support an objective consideration of player evaluation and assessment. Representative performance tests would enable coaches to objectively view kick difficulty and support a fairer assessment of player performance output through the incorporation of context in task design (Quarrie & Hopkins, 2015). For instance, if a player had three kicks during a game and only one was effective, their kicking efficiency would be rated at 33% and well below average, without any context provided. However, coaches need to consider the constraints placed on the individual kicks to ascertain whether all three kicks resulted from winning the ball from a stoppage, with the performer being under pressure and in possession of the ball for less than two secs, whilst making a short kick. Under these performance constraints an average value of expected kicking effectiveness would be 14.6% (Figure 4), offering a very different perspective on player performance.

Constraints interaction was measured with the rule induction approach which included five constraints, advancing the specification of rules in the study by Robertson, et al. (2018), who included only three constraints. Despite these small methodological differences, the findings align with data observed within the elite AF competition level (Robertson, et al., 2018). Confidence levels in effective kicks in both studies are within the 80-90% range and suggest that players perform better when kicking over shorter distances to an open target (e.g., an unmarked teammate or space on-field). Similar to findings reported by Robertson, et al. (2018), the top five rules for effective kicks, are conducted under no pressure, from a kick < 40 metres and a majority from either a mark or a free kick. Within AF competitions, a mark and free kick are the only circumstances where possession can be taken without physical pressure being applied by the opposition. Conversely, for ineffective kicks, similar rules had a greater range in their confidence levels, ranging from 15% to 39% compared to the range of 38 to 45% in Robertson, et al. (2018). This study revealed that the most common circumstances whereby an ineffective kick emerged was from possession sources related to open play situations. This observation combined with the short time in possession for ineffective kicks, could lead to speculation that players potentially do not have the skillset to gather or receive the ball under severe time constraints to kick effectively to a covered target (e.g., marked teammate or space). The differences between the findings of this study and other investigations of performance in AF may be due to a range of factors such as skill level, decision-making abilities, age and experience of the participant sample studied (Abernethy, 1988; Royal, et al., 2006; Williams, 2000).

Understanding differences between tiers is crucial for creating a training design which is representative of the tier. Analysis of performance between tiers resulted in seven unique rules, four rules shared between two tiers and five rules found across all tiers (Figure 5). Of all ten AFL rules identified by our methods, seven were found to be operative in either the state leagues or the U18 tier. Two of the three unique rules found in the AFL, included a kick target of a covered or leading player, which was found in only four rules produced by all three tiers. Kicking to a covered or leading target could be a more difficult kick to execute and, thus, it is somewhat unsurprising that they are found in two rules unique to the elite AFL competition. Between the U18 and state leagues tiers, greater variation exists in the nature of the seven shared rules. The state leagues were ranked more highly in four rules based on levels of confidence (Figure 5). Three rules contained constraints which come from an open play style of possession source (i.e., handball receive or groundball). Although conjecture, often in match conditions, these possession types have more pressure as they take place in dynamic, open play situations. The present findings are similar to those reported in other sports, where athletes from higher performance levels display improved skill performance outcomes compared to lower tiers (Smith, et al., 1992). The ability to cope in these situations may be due to individual factors, including the age, learning, development and greater practice and performance experiences of these more skilled individuals (Renshaw, Chow, Davids, & Hammond, 2010). Incorporating individual constraints may also aid in understanding differences and development between sub-elite and elite players.

Understanding how athletes maintain their skill level under competitive performance conditions, and how this differs across performance tiers is essential knowledge for sports practitioners seeking to enhance the effectiveness and efficiency of training designs and transfer between practice and competition (Pinder, et al., 2011; Pocock, et al., 2018; Robertson, et al., 2018). Accounting for different performance tiers facilitates the adoption of targeted and representative training designs for athlete preparation, aligned with their developmental status, as opposed to attempting to use generic training designs which may be more suitable for athletes in other competitive performance tiers. As demonstrated in Figure 5 and as observed in differences with data reported by Robertson, et al. (2018), the importance for accounting for influence of performance tier is vital to designing representative training environments. Differences in skilled performance exist at different tiers, potentially due to the changing prevalence and interaction of constraints. Thus, data obtained on performance from one tier cannot be transferred to the design of practice tasks for athletes in another competitive level due to specificity and representativeness of training designs. This observation emphasises the importance of understanding the specific athlete-environment interactions that occur in competitive performance conditions to develop a representative training designs (Pinder, et al., 2011).

A rules based approach may provide an objective tool to help quantify the level of representativeness within a practice task design which can complement existing subjective approaches, which rely on experiential knowledge of elite sport practitioners (Krause, Farrow, Reid, Buszard, & Pinder, 2018; Pocock, et al., 2018; Robertson, et al., 2018). This could improve the effectiveness and efficiency of designing training tasks which replicate competition environments, allowing them to target specific strengths and weaknesses within training, based on competition tier (Pinder, et al., 2011; Robertson, et al., 2018). This information could be used by coaches in multiple ways. First, they could seek to incorporate a constraints-led approach into their training design to create more challenging and realistic practice task designs where athletes are faced with these competition-environment constraints (Pinder, et al., 2011). Alternatively, this type of design may afford opportunities for performers to experience a strategic effect on decision-making processes.

Given the increasing availability of larger datasets there is scope for future research to develop both team and individual-specific performance models to facilitate specificity of training designs. The power of these models could be enhanced by adding further constraints and contextual variables, such as such as physical output, field location and score margin of kicks to improve the predicted outcomes of skilled actions, and the representativeness of training designs (Ávila-Moreno, Chirosa-Ríos, Ureña-Espá, Lozano-Jarque, & Ulloa-Díaz, 2018; Royal, et al., 2006). Feasibility of incorporating a large number of contextual variables and constraints into performance analysis can be limited due to challenges of interpreting large volumes of data in a time effective manner (Couceiro, Dias, Araújo, & Davids, 2016). Large datasets can impose some feasibility issues around data management. In the current study 5,060 (17%) kicks were missing a measurement for at least one of the seven constraints. Further, differences in sample sizes of kicks collected at each performance tier meant that some rules found in the smaller dataset had the potential to be more prevalent due to a bias from the competitive games analysed. Additionally, due to the manual treatment of discrete constraints, some constraints contained just two levels (i.e., kick distance) and others five (i.e., possession source), a potential for bias in rule frequencies exists due to the number of options within a specific constraint. Future research could use a continuous scale or fuzzy approaches to help account for this potential bias (Cariñena, 2014). Automated capture of data through deep learning and computer vision may aid in reducing time required and alleviate issues around manual data collection and interpretation (Couceiro, et al., 2016; Robertson, et al., 2018).

Conclusion

This study compared the variations in constraint interactions upon kicking action outcomes in AF across three different performance tiers. When effects of constraints are viewed in isolation, or pairs, they can offer some insight into what a player is experiencing in specific performance contexts. However, when all (or many) constraints are considered, a more complete picture can be provided. Rule induction provides a method capable of determining high frequency events and their outcomes. Findings from this analytics approach in research can be used to assess kicking performance of players, providing greater performance context to aid interpretation by practitioners. This information may then be used for player selection and recruitment purposes. The methodologies presented are not limited to kicking constraints, as sport specific constraints can be used to gain further understanding of performance conditions across a range of team sports. This analytics methodology may better inform and objectively define key events competitive performance which can be simulated in training, and make using a RLD framework more effective and efficient. Whilst there are specificities in differences between rules of AF and other team sports, the current findings cannot be transferred to other sports. However, the analytic methods presented here can be. Understanding how the interaction of constraints differs across performance tiers is vital to creating a representative design specific for player assessment and practice task composition for specific competitive performance tiers.

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References

Abernethy, B. (1988). The effects of age and expertise upon perceptual skill development in a racquet sport. *Research quarterly for exercise and sport*, *59*, 210-221.

Agarwal, R., & Srikant, R. (1994). Fast algorithms for mining association rules. In *Proc. of the 20th VLDB Conference* (pp. 487-499).

Araújo, D., & Davids, K. (2018). The (Sport) Performer-Environment System as the Base Unit in Explanations of Expert Performance. *Journal of Expertise/December*, *1*.

Araújo, D., Davids, K., Bennett, S. J., Button, C., & Chapman, G. (2004). Emergence of sport skills under constraints. In A. M. Williams & N. J. Hodges (Eds.), *Skill acquisition in sport: Research, theory and practice* (pp. 409): Routledge.

Ávila-Moreno, F. M., Chirosa-Ríos, L. J., Ureña-Espá, A., Lozano-Jarque, D., & Ulloa-Díaz, D. (2018). Evaluation of tactical performance in invasion team sports: a systematic review. *International Journal of Performance Analysis in Sport*, 1-22.

Buchheit, M., Mendez-Villanueva, A., Simpson, B., & Bourdon, P. (2010). Match running performance and fitness in youth soccer. *International journal of sports medicine*, *31*, 818-825.

Cariñena, P. (2014). Fuzzy temporal association rules: combining temporal and quantitative data to increase rule expressiveness. *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery*, *4*, 64-70.

Couceiro, M. S., Dias, G., Araújo, D., & Davids, K. (2016). The ARCANE project: how an ecological dynamics framework can enhance performance assessment and prediction in football. *Sports Medicine*, *46*, 1781-1786.

Davids, K., Button, C., Araújo, D., Renshaw, I., & Hristovski, R. (2006). Movement models from sports provide representative task constraints for studying adaptive behavior in human movement systems. *Adaptive behavior*, *14*, 73-95.

Davids, K., Button, C., & Bennet, S. (2008). *Dynamics of skill acquisition: a constraints-led approach*: Human Kinetics.

Dudek, D. (2010). Measures for Comparing Association Rule Sets. In *International Conference on Artificial Intelligence and Soft Computing* (pp. 315-322). Berlin, Heidelberg: Springer Berlin Heidelberg.

Farrow, D., & Reid, M. (2010). The effect of equipment scaling on the skill acquisition of beginning tennis players. *Journal of sports sciences*, *28*, 723-732.

Farrow, D., & Robertson, S. (2017). Development of a skill acquisition periodisation framework for high-performance sport. *Sports Medicine*, *47*, 1043-1054.

Goldman, M., & Rao, J. M. (2012). Effort vs. concentration: the asymmetric impact of pressure on NBA performance. In *Proceedings of the mit sloan sports analytics conference* (pp. 1-10).

Gray, A. J., & Jenkins, D. G. (2010). Match analysis and the physiological demands of Australian football. *Sports Medicine*, *40*, 347-360.

Gudmundsson, J., & Horton, M. (2016). Spatio-Temporal Analysis of Team Sports - A Survey. *arXiv 1602.06994*.

Hahsler, M., Buchta, C., Gruen, B., & Hornik, K. (2018). Package ‘arules’.

Johnston, R., Watsford, M., Pine, M., Spurrs, R., Murphy, A., & Pruyn, E. (2012). Movement demands and match performance in professional Australian football. *International journal of sports medicine*, *33*, 89-93.

Krause, L., Farrow, D., Reid, M., Buszard, T., & Pinder, R. (2018). Helping coaches apply the principles of representative learning design: validation of a tennis specific practice assessment tool. *Journal of sports sciences*, *36*, 1277-1286.

Mccosker, C., Renshaw, I., Greenwood, D., Davids, K., & Gosden, E. (2019). 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*, 1-9.

Mohr, M., Krustrup, P., Andersson, H., Kirkendal, D., & Bangsbo, J. (2008). Match activities of elite women soccer players at different performance levels. *The Journal of Strength & Conditioning Research*, *22*, 341-349.

Morgan, S. (2011). Detecting Spatial Trends in Hockey Using Frequent Item Sets. In *Proceedings of the 8th International Symposium on Computer Science in Sport* (pp. 58-61).

Newell, K. M. (1986). Constraints on the development of coordination. *Motor development in children: Aspects of coordination and control*, *34*, 341-360.

Pinder, R., Davids, K., Renshaw, I., & Araújo, D. (2011). Representative learning design and functionality of research and practice in sport. *Journal of Sport and Exercise Psychology*, *33*, 146-155.

Pocock, C., Bezodis, N. E., Davids, K., & North, J. S. (2018). 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*, 1-8.

Quarrie, K. L., & Hopkins, W. G. (2015). Evaluation of goal kicking performance in international rugby union matches. *Journal of Science and Medicine in Sport*, *18*, 195-198.

Reich, B. J., Hodges, J. S., Carlin, B. P., & Reich, A. M. (2006). A spatial analysis of basketball shot chart data. *The American Statistician*, *60*, 3-12.

Renshaw, I., Chow, J. Y., Davids, K., & Hammond, J. (2010). A constraints-led perspective to understanding skill acquisition and game play: A basis for integration of motor learning theory and physical education praxis? *Physical Education and Sport Pedagogy*, *15*, 117-137.

Renshaw, I., Davids, K., Newcombe, D., & Roberts, W. (2019). *The Constraints-Led Approach: Principles for Sports Coaching and Practice Design* (1st ed.). London: Routledge.

Robertson, S., Spencer, B., Back, N., & Farrow, D. (2018). A rule induction framework for the determination of representative learning design in skilled performance. *Journal of Sport Science*.

Royal, K. A., Farrow, D., Mujika, I., Halson, S. L., Pyne, D., & Abernethy, B. (2006). The effects of fatigue on decision making and shooting skill performance in water polo players. *Journal of sports sciences*, *24*, 807-815.

Smith, D., Roberts, D., & Watson, B. (1992). Physical, physiological and performance differences between Canadian national team and universiade volleyball players. *Journal of sports sciences*, *10*, 131-138.

Vilar, L., Araújo, D., Davids, K., & Renshaw, I. (2012). The need for 'representative task design'in evaluating efficacy of skills tests in sport: A comment on Russell, Benton and Kingsley (2010). *Journal of sports sciences*, *30*, 1727-1730.

Williams, A. M. (2000). Perceptual skill in soccer: Implications for talent identification and development. *Journal of sports sciences*, *18*, 737-750.

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**

Figure 1. Breakdown of categories of constraint and their levels. Each kick is assigned one value from each category.

Figure 2. Mean effectiveness (%) and 95% confidence interval (CI) of kicks by constraint type. 3a) Distance of kicks less than 40 and greater than 40 metres. 3b) Pressure types of chase, frontal, physical or no pressure. 3c) Source of possession: stoppage, ground ball, Handball received, free kick or mark. 3d) Kick target of a covered, leading or open player. 3e) time in possession measured in seconds, 0<2, 2<4, 4<6 and 6+ seconds. 3f) Player velocity at kick: sprint, run or stationary.

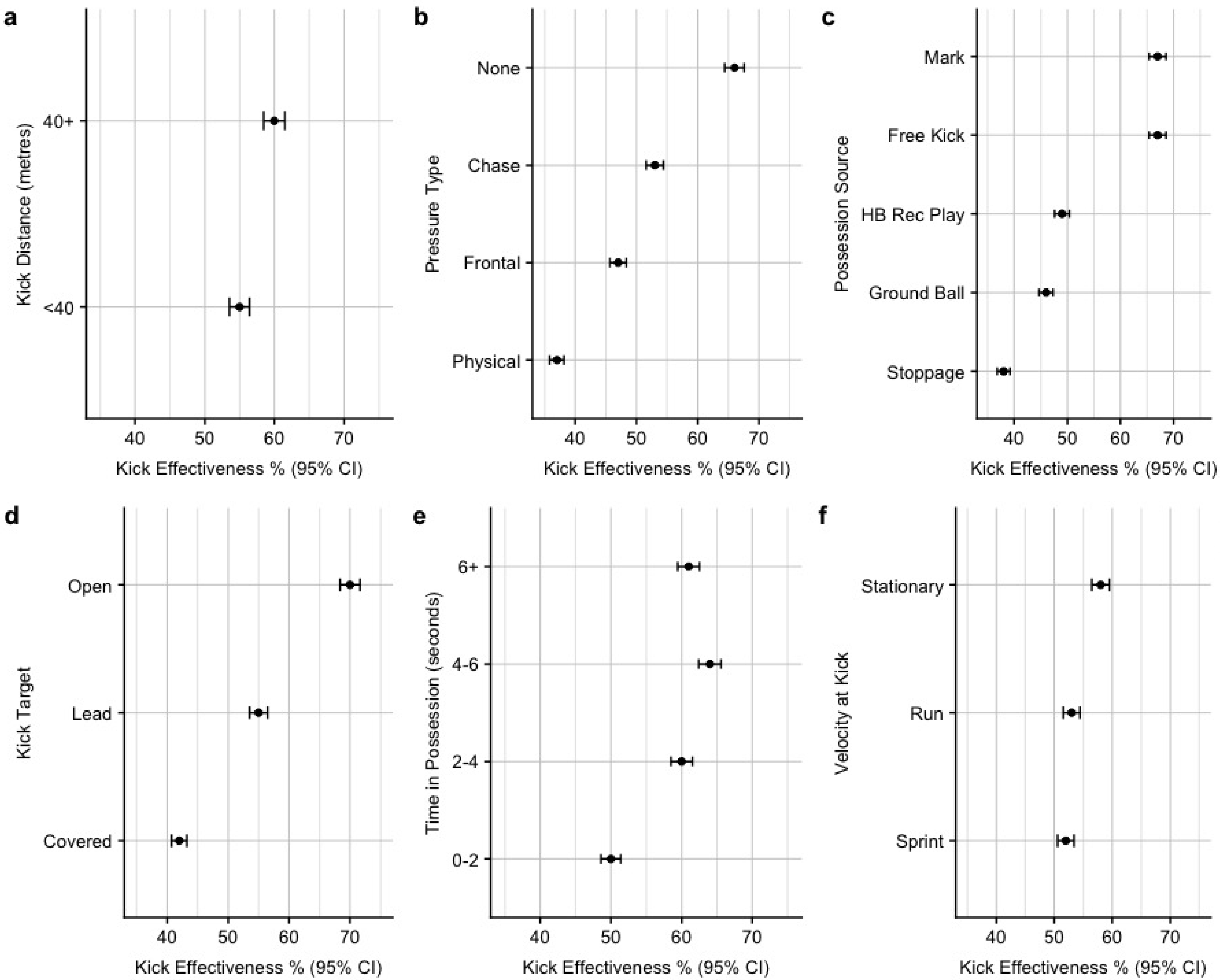
Figure 3. Bi-variate example of the interaction of two constraints. Dotted line represents the average kicking effectiveness without taking constraints into account (54%). a) Disposal pressure type by time in possession. b) Time in possession and kick distance.

Figure 4. Multi-variate analysis results of rules associated with kick outcome. The five rules most strongly associated with effective (green) and ineffective kicks (red) are ranked by the highest and lowest confidence values. Where a tick represents the presence of the performance context within the rule.

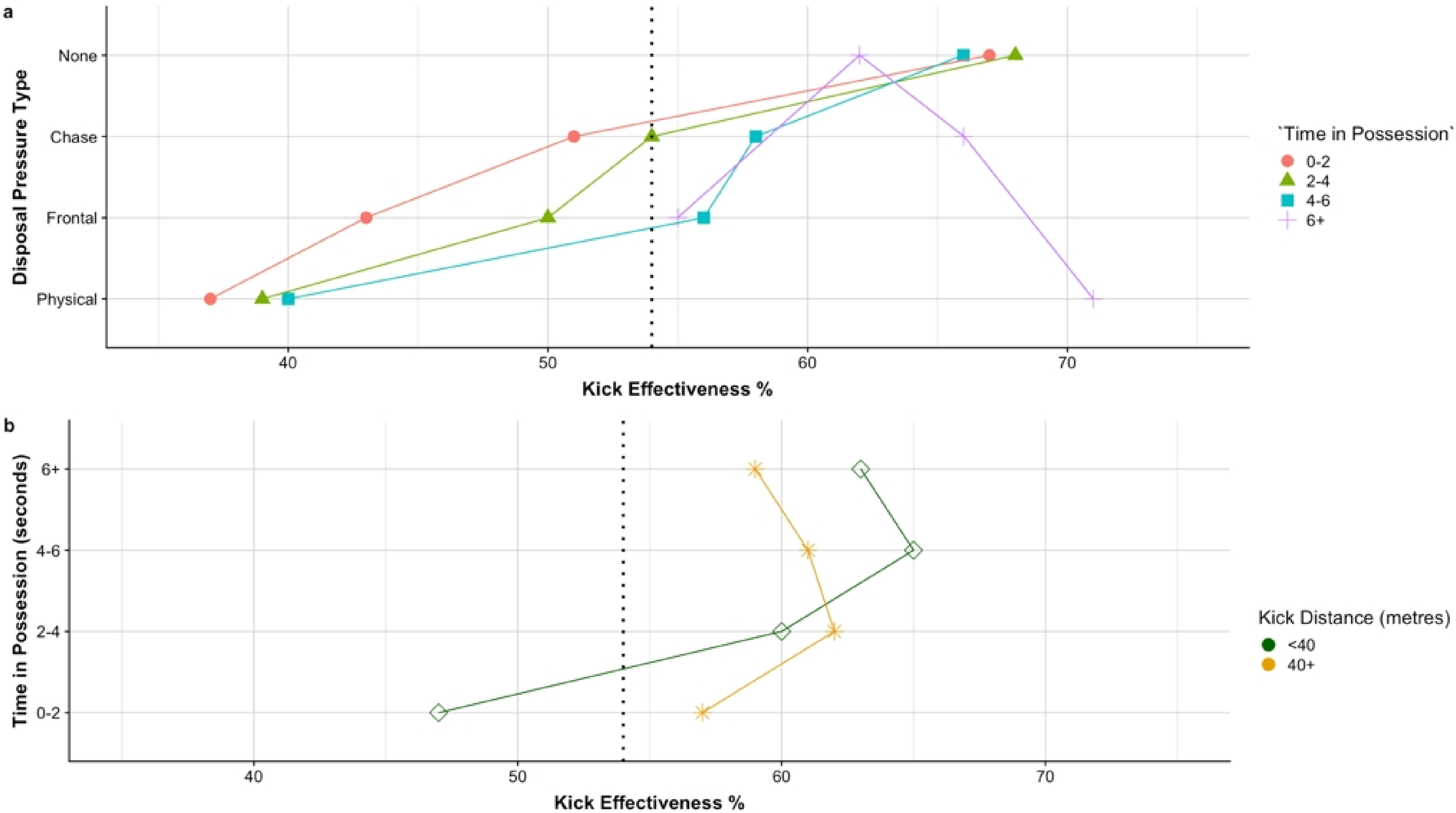
Figure 5. Rule based comparison between levels of competition. The top 10 rules based on confidence are displayed and ordered by constraint type. Grey circles indicate that the rule was not present in the top ten rules for that tier.

Figure 6. Example of how adding additional constraint variables and considering the constraint interaction alters the mean efficiency of the kick outcome. Percentage values indicate confidence level of an effective kick.


Source
Ground ball
Mark / free kick
Handball receive
Stoppage
Kick distance
< 40 m
> 40 m
Pressure
None
Chase
Frontal
Physical
Possession time
< 2 secs
2 - 4 secs
4 - 6 secs
6+ secs
Velocity
Running
Stationary
Target
Open
Covered



a
Kick Distance (metres)
40+
<40
40
50
60
70
Kick Effectiveness % (95% CI)
b
Pressure Type
None
Chase
Frontal
Physical
40
50
60
70
Kick Effectiveness % (95% CI)
c
Possession Source
Mark
Free Kick
HB Rec Play
Ground Ball
Stoppage
40
50
60
70
Kick Effectiveness % (95% CI)
d
Kick Target
Open
Lead
Covered
40
50
60
70
Kick Effectiveness % (95% CI)
e
Time in Possession (seconds)
6+
4-6
2-4
0-2
40
50
60
70
Kick Effectiveness % (95% CI)
f
Velocity at Kick
Stationary
Run
Sprint
40
50
60
70
Kick Effectiveness % (95% CI)

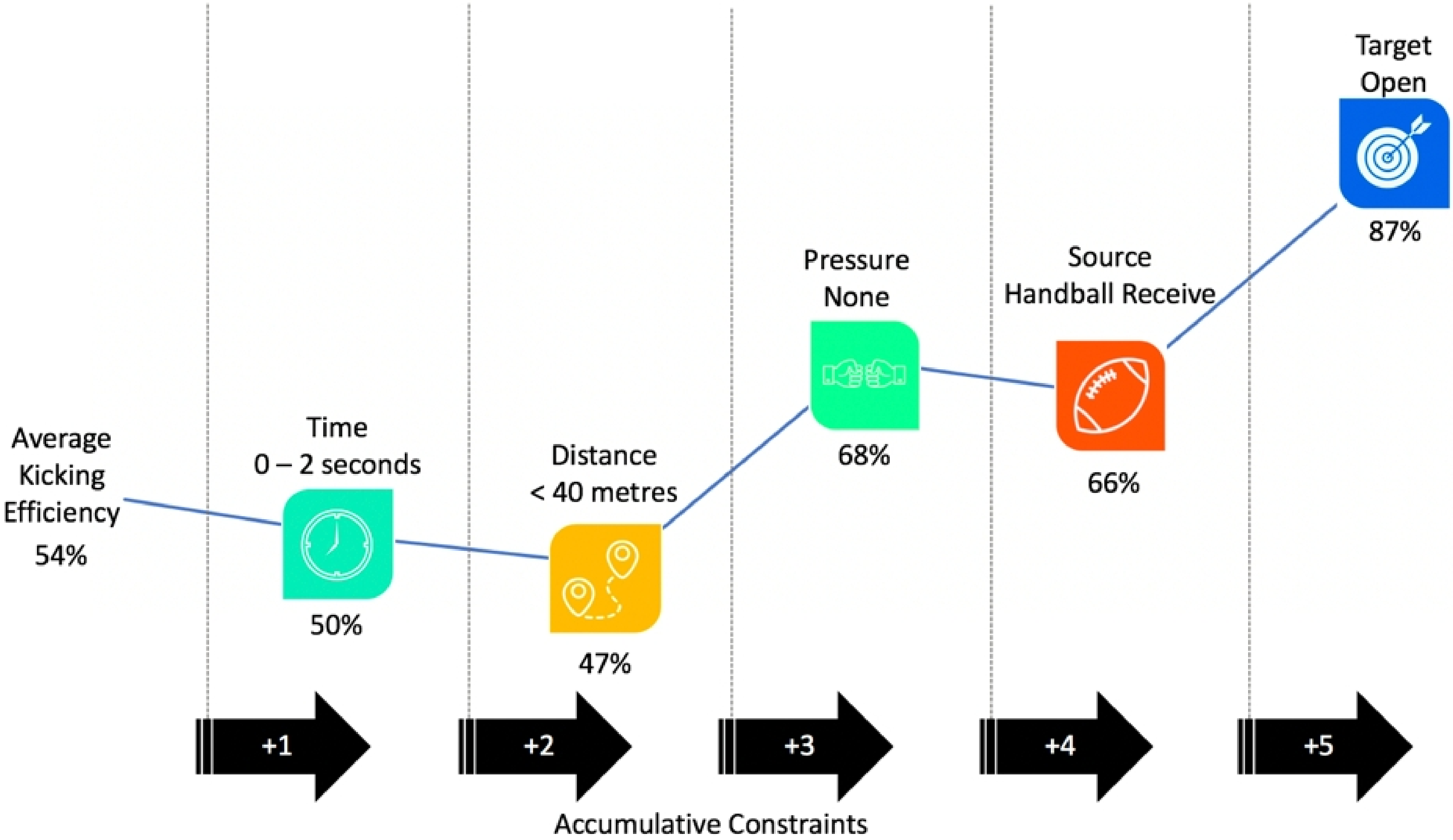


a
Disposal Pressure Type
None
Chase
Frontal
Physical
40
50
60
70
Kick Effectiveness %
`Time in Possession`
0-2
2-4
4-6
6+
b
Time in Possession (seconds)
6+
4-6
2-4
0-2
40
50
60
70
Kick Effectiveness %
Kick Distance (metres)
<40
40+

Time			Distance		Pressure				Target		Source					Effective kick confidence levels
0-2	2-4	4-6	< 40	40 +	Physical	Frontal	Chase	None	Open	Covered	Free Kick	Stoppage	Ground Ball	HB Received	Mark	
	✓		✓					✓	✓						✓	87.0%
✓			✓					✓	✓					✓		86.9%
		✓	✓					✓	✓						✓	86.6%
✓			✓					✓	✓						✓	84.1%
	✓		✓					✓	✓		✓					83.3%

Time			Distance		Pressure				Target		Source					Effective kick confidence levels
0-2	2-4	4-6	< 40	40 +	Physical	Frontal	Chase	None	Open	Covered	Free Kick	Stoppage	Ground Ball	HB Received	Mark	
✓			✓		✓					✓		✓				14.6%
✓			✓		✓					✓			✓			15.4%
✓			✓			✓				✓				✓		23.3%
✓			✓			✓				✓			✓			23.3%
✓			✓				✓			✓				✓		38.5%

Source	Kick Distance	Target	Pressure	Time in Possession	U18	State Leagues	AFL
					Confidence (%)		
Free Kick	<40	Open	None	0-2	83		
Free Kick	<40	Open	None	2-4	82	82	94
Free Kick	<40	Open	None	4-6	72		
Free Kick	<40	Open	None	6+		82	92
Free Kick	40+	Covered	None	6+		90	84
Ground Ball	<40	Open	None	0-2	72	78	
Ground Ball	<40	Open	Frontal	2-4		72	
HB Rec Play	<40	Open	None	0-2	82	88	94
HB Rec Play	<40	Open	None	2-4	72		
Mark	<40	Open	None	0-2	82	73	100
Mark	<40	Lead	None	0-2			81
Mark	<40	Open	None	2-4	85	83	97
Mark	<40	Covered	None	2-4			77
Mark	<40	Open	None	4-6	83	79	97
Mark	<40	Lead	None	4-6	72	74	
Mark	<40	Open	None	6+			86


Average Kicking Efficiency
54%
Time
0 – 2 seconds
50%
Distance
< 40 metres
47%
Pressure
None
68%
Source
Handball Receive
66%
Target
Open
87%
+1
+2
+3
+4
+5
Accumulative Constraints