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The influence of environmental and task constraint interaction on skilled behaviour in Australian Football

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ABSTRACT

The design of sports practice environments can be informed through data collected and analysed according to principles of the constraints-led approach. In this study, three manipulated environmental (area per player, number of players and team outnumber) and two task (activity objective and disposal limitations) constraints were measured during professional Australian Football training activities ($n = 112$) to determine their relationship with skilled behaviour. Linear regression modelling of the five manipulated constraints explained 68% of the variance in disposal frequency but only 22% in skill efficiency. Activities with scoring objectives, limited to kicking or which permitted all disposals, reduced the disposal frequency per player. Activities which permitted all disposals were also weakly, negatively associated with skill efficiency. A Classification Based on Association analysis measured the interaction between manipulated constraints and their relationships with possession time and pressure. When compared to the null model, the analysis improved pressure classification accuracy by 5.9% and did not improve possession time classification accuracy. This indicates skills were often performed under varying spatial and temporal constraints during many of the training activities. This study presents multivariate analytical methods which consider constraint interaction, enhancing how practitioners can evaluate and inform training design in sport.

KEYWORDS
Team sport; coaching; training; performance analysis; constraints-led approach

Introduction

Designing practice environments that support athlete learning and improve performance is an important consideration for sports practitioners (Davids, 2012). A framework commonly used to guide the design of such practice environments is the constraints-led approach (Newell, 1986). In this framework, constraints are viewed as boundaries, occurring over varying timescales, that shape emergent behaviour of individuals and groups (Newell, Liu, & Mayer-Kress, 2001). Constraints can be categorised into task, performer and environmental classes (Newell, 1986). In sport, task constraints relate to the intent of the activity, inclusive of the rules or equipment used. Performer constraints pertain to the individual, including their anthropometric attributes and physiological qualities. Environmental constraints typically include features external to the performer, and may include the weather, lighting or field dimensions (Newell, 1986).

By identifying constraints which are most influential on athlete behaviours during competition, practitioners can carefully design them into practice tasks – amplifying or dampening them to help channel or guide certain behaviours during training (Renshaw, Chow, Davids, & Hammond, 2010). These manipulations should encourage problem-solving and facilitate athlete-environment interactions (Woods et al., 2020). Evaluation of these manipulations can then determine whether the desired behavioural outcome is being functionally achieved. Athlete behaviour responses to the intentional manipulation of constraints in practice design have been examined across a variety of sports. For example, manipulations of field size can be inversely related to the frequency of some team-sport actions, such as interceptions, shots on goal or tackles (Casamichana & Castellano, 2010; Fleay, Joyce, Banyard, & Woods, 2018). Decreasing the number of players in a practice task can increase the number of actions performed per player, such as (un)successful passes or dribbles (Sarmento et al., 2018; Timmerman, Savelsbergh, & Farrow, 2019), while creating a team imbalance (i.e. 6 vs. 5) may increase the proportion of successful passes completed in Australian Football (AF) small side games (Bonney, Ball, Berry, & Larkin, 2020).

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An ongoing methodological challenge in the modelling of athlete behaviour during training and competition is that constraints do not function in isolation, but interact dynamically and often non-linearly (Newell, 1986). For example, in youth football, playing space and the distance between players may be influenced by the interaction of field dimensions (environmental constraint), skill level (performer constraint) and playing numbers (task constraint) (Silva et al., 2014, 2015). In field hockey, both field characteristics and playing numbers influenced action frequencies – increasing or decreasing them based on the emergent time and task goals (Timmerman et al., 2019). Considering how constraints interact may provide practitioners with greater context, potentially improving their understanding on how they can design training environments to facilitate athlete learning. Therefore, measuring multiple constraints and utilising analytical methods which account for these interactions is recommended (Browne, Sweeting, Davids, & Robertson, 2019; Robertson, Spencer, Back, & Farrow, 2019). Practically, constraint measurement is typically limited by resources and costs, meaning no model can be fully complete. However, as the feasibility of capturing constraints in the field is increased due to technological improvements, furthering this methodology presents a worthwhile exercise. Rule induction represents one such analysis approach that is fit for the purpose of this exercise. Specifically, it focusses on identifying the most commonly occurring and influential patterns in data, an approach that closely matches the human method of heuristics (Agrawal, Mannila, Srikant, Toivonen, & Verkamo, 1996). In a scenario of growing data volume, this encourages the user to focus on only those non-linear interactions which are most important in terms of modelling a phenomenon of interest.

A rule induction method for analysing constraint interaction was recently utilised to evaluate kicks during AF match play (Robertson et al., 2019) and has been contrasted with univariate analysis (Browne et al., 2019). For example, Browne et al. (2019) noted that when compared with univariate analysis, rule induction provided a more comprehensive insight into the kicking performance of Australian footballers. This was manifest in kicks under physical pressure being more accurate when coupled with task constraints of longer possession time and kicks to targets that were unmarked or unopposed. Using similar analysis, the current study aims to ascertain the strength of relationship between task and environmental constraints manipulated as part of the training design, and (a) their effects on the frequency and effectiveness of skill involvements, and (b) the prevalence of constraints on skill involvements.

Methodology

Participants

Participants were listed players ($n = 43$; 24.2 ± 3.5 y; 186.8 ± 7.7 cm; 84 ± 7.8 kg) from one professional AF club. All participants provided written informed consent and were injury free at the time of participation in the selected activities. Ethical approval was obtained from the University Ethics Committee.

Data collection

Data collection occurred during the club's 2020 Australian Football League pre-season training period. Training activities ($n = 112$) with environmental and task constraint manipulations were captured, consisting of 20 different activity types and 3907 skill involvements. To obtain information on training design, five manipulated constraints were used: three environmental and two task constraints (Figure 1). The constraints selected were based on the literature (Bonney et al., 2020; Timmerman et al., 2019) and consultation with expert AF coaches at the club. For each drill, the total number of players and team outnumber were recorded, with the field dimensions manually recorded using a measuring wheel. Activity objective (i.e. possession or scoring) and disposal limitation (i.e. handballs, kicking or all disposals) were additionally recorded.

To record each skill involvement, activities were filmed at 25 Hz with a two-dimensional camera (Canon XA25/Canon XA20) from either a side-on or behind-the-goals perspective. Cameras were situated in a fixed position and vision angle varied depending on location of drill at the time of performance. To quantify skill involvements and the surrounding task constraints,

Figure 1. Manipulated environmental and task constraints (left) and constraints on skill involvements (right) with associated levels where appropriate.

notational analysis software was used (Sportscode, version 12.2.10, Hudl). A customised code window was created whereby each skill involvement was recorded according to "type" (kick or handball) and "outcome" (effective or ineffective). The effectiveness of the skill involvement was defined in accordance with Champion Data (Melbourne, Pty Ltd), with a handball or kick <40 m deemed effective, if the intended target retained ball possession. A kick >40 m was deemed effective if kicked to a 50/50 contest or outnumber to the advantage of the attacking team. Effectiveness was represented as skill efficiency (%), defined as the number of effective skill involvements in each drill relative to the total number of skill involvements. Disposal frequency was represented as the total number of disposals relative to the duration of the activity and the number of players in the activity (disposals/min/player). To capture the task constraints on each skill involvement, the Sportscode window was used to add additional labels, defined through consultation with club coaches and adapted from the literature (Robertson et al., 2019). As shown in Figure 1, time in possession was discretised into two groups; <2 s or ≥2 s and pressure was categorised as present or absent. Pressure was defined by the presence of an opposition player within 3 m of the passer at moment of ball disposal (Robertson et al., 2019). Efficiency, disposal frequency, time in possession and pressure were then exported, according to their drill, into a custom Microsoft Excel spreadsheet. Constraint manipulation data and skill involvement data were then joined according to the training activity, forming a single database.

To assess the intra-rater reliability of the skill involvement coding, three activities consisting of 145 involvements were coded on two separate occasions with at least 14 days between. The Kappa statistic was used to assess intra-rater reliability of each variable (Landis & Koch, 1977). Agreement was "almost perfect" for the time in possession (0.83) and effectiveness (0.93) and "substantial" for pressure (0.79).

Statistical analysis

All statistical analysis occurred in R (R Core Team, 2019). To address the first aim, two multiple linear regression models were used to determine the relationship between the manipulated environmental constraints (area per player, number of players and team outnumber) and task constraints (drill objective and disposal limitations) and their effect on (a) disposal frequency and (b) skill efficiency.

To determine the influence of task and environmental constraints on the time in possession and pressure of each skill involvement, a Classification Based on Association (Liu, Hsu, & Ma, 1998) approach was utilised. The Classification Based on Association (Liu et al., 1998) creates a model to predict the class of a variable based upon association rules mined in a dataset. A default rule is also generated in the model for which a class prediction is made for items which do not meet the mined rules. Each rule is presented with associated support and confidence levels. Support (%) is a measure for how frequently a rule appeared in the database and confidence (%) measures the frequency of a class, given the associated rule.

The *ArulesCBA* package (Hahsler & Johnson, 2020) was used to run the *CBA* algorithm (Liu et al., 1998) to construct two models; classification of time in possession and pressure. A random sample of 70% (2734 skill involvements) of the dataset was selected for classifier training. To prepare the data for analysis, discretisation of the area per player, number of players and team outnumber variables was conducted through the *ArulesCBA* package which used the minimum description length principle to bin data. The breaks for each discretisation in the time in possession model were: area per player; 93, 249, 276, 267, 590, number of players; 15 and team outnumber; 1, 4.5. The breaks for each discretisation in the pressure model were: area per player; 131, 235, 263, 276, 451, 522, number of players; 9 and team outnumber; 4.5. Parameters for both constructed models were set with a minimum support of 0.03 and minimum confidence of 0.5. Both models were required to use rules with five items representing each of the manipulated constraints and pruning occurred with the M1 method. The models constructed from the training data were then used to predict the classification of time in possession and pressure on the remaining 30% (1173 skill involvements) of the dataset. Classification accuracy of the two models were evaluated with a confusion matrix.

Results

All descriptive statistics are reported as a mean and standard deviation. Across all activities, the mean area per player was 338 ± 269 m^2, mean number of players was 12 ± 4.3 and mean team outnumber was 0.7 ± 1.2. Within the dataset, 40% of activities were limited to handballs, 12% were limited to kicks and 48% permitted all disposals. Activities with possession-based objectives comprised 15% of the dataset whilst activities with scoring-based objectives were 85%. Mean skill efficiency across all activities was 80.9 ± 9.13% and mean disposals per player per minute was 0.81 ± 0.38.

As displayed in Table 1, the linear regression models showed the manipulated environmental and task constraints had a stronger relationship with disposal

Table 1. Results of multiple linear regression analysis between manipulated environmental and task constraints and disposal frequency (Model 1) and skill efficiency (Model 2).

	Model 1 Disposal frequency			Model 2 Skill efficiency		
	B	SE	*t*	*B*	SE	*t*
(Intercept)	1.880 ***	0.145	12.954	93.596 ***	5.508	16.992
Area per player (m^2)	0.0001	0.0001	1.079	0.007	0.006	1.123
Number of players	−0.014 *	0.006	−2.436	−0.163	0.218	−0.748
Team outnumber	0.014	0.021	0.646	1.373	0.815	1.685
Activity objective: scoring[a]	−0.632 ***	0.150	−4.220	−7.435	5.682	−1.309
Disposal limits: kicking[b]	−0.945 ***	0.171	−5.536	−14.753 *	6.480	−2.277
Disposal limits: no limits[b]	−0.707 ***	0.095	−7.475	−12.582 ***	3.593	−3.502
Adjusted R^2	0.679			0.216		

***$p < 0.001$, **$p < 0.01$, *$p < 0.05$.
B = coefficient, SE = standard error of the coefficient, t = test statistic.
[a]Activity objective: possession used as reference category.
[b]Disposal limits: handballs used as reference category.

frequency (Adjusted $R^2 = 0.679$) than skill efficiency (Adjusted $R^2 = 0.216$). The relationship between manipulated constraints and disposal frequency and skill efficiency is visualised in Figure 2. Activities permitting all disposals ($t = -7.475$), limited to kicking only ($t = -5.536$) or with a scoring objective ($t = -4.220$) had strong negative relationships with disposal frequency. Area per player ($t = 1.079$) and team outnumber ($t = 0.646$) had weak positive associations with disposal frequency (Table 1). Activities permitting all disposals ($t = -3.502$) also had a strong negative relationship with skill efficiency. Area per player ($t = 1.123$), the number of players ($t = -0.748$), team outnumber ($t = 1.685$) and scoring objectives ($t = -1.309$) each had weak associations with skill efficiency (Table 1).

For the time in possession constraint, the proportion of each class was: <2 s = 66% and ≥2 s = 34%. For the pressure constraint, each class was: None = 58% and Pressure = 42%. The time in possession classifier resulted in seven rules, and the pressure classifier five, as displayed in Table 2. Excluding the default rule, which makes a prediction for items which do not meet the rules produced in the model, rules produced to classify time in possession ranged from 60% to 95% confidence. Rules to classify pressure ranged from 74% to 84% confidence. The confusion matrix revealed the time in possession and pressure classifiers had accuracies of 66% and 63.9%, respectively. Using the majority constraint class in the dataset (<2 s = 66%) as a threshold, the time in possession classifier did not improve class prediction accuracy. However, the pressure classifier slightly improved class prediction accuracy (+5.9%), compared to the majority constraint class (None = 58%).

Discussion

This study demonstrated how environmental and task constraint manipulations can be evaluated to determine their influence on skilled behaviour in AF. The constraints manipulated in the current study were more influential on disposal frequency than skill efficiency, with disposal frequency more predictable than skill efficiency. Further, using an analysis approach such as Classification Based on Association highlighted the non-linearity of constraint interaction. The analysis only slightly improved, upon the majority class threshold, the classification accuracy of pressure and did not improve possession time classification accuracy. This demonstrated the tendency for activities to comprise skill involvements in different classes of constraints, indicating variable participant behaviour. This means participants were exposed to skill involvements in a range of performance contexts. Measurement of athlete skill variability can assist practitioners to evaluate if training aims are being achieved.

Linear regression modelling was used to determine the relationship between manipulated task and environmental constraints and disposal frequency, explaining 67.9% of the variance in disposal frequency. This result highlights the capability of models to predict, with some certainty, the disposal frequency of players in activities. This information could be beneficial for practitioners when estimating skill volumes, which has application for planning training designs (Farrow & Robertson, 2017) and prescribing training loads for rehabilitating athletes. A caveat to this application is that behaviour will still vary between players, manifest through things like playing position, ability, age (Almeida, Duarte, Volossovitch, & Ferreira, 2016), height (Cordovil et al., 2009), and/or previous experience (Pocock, Bezodis, Davids, & North, 2018), which will require consideration. This caveat serves as an important avenue for future work to extend on the current findings. Area per player did not influence disposal frequency, which is in agreement with similar work in AF

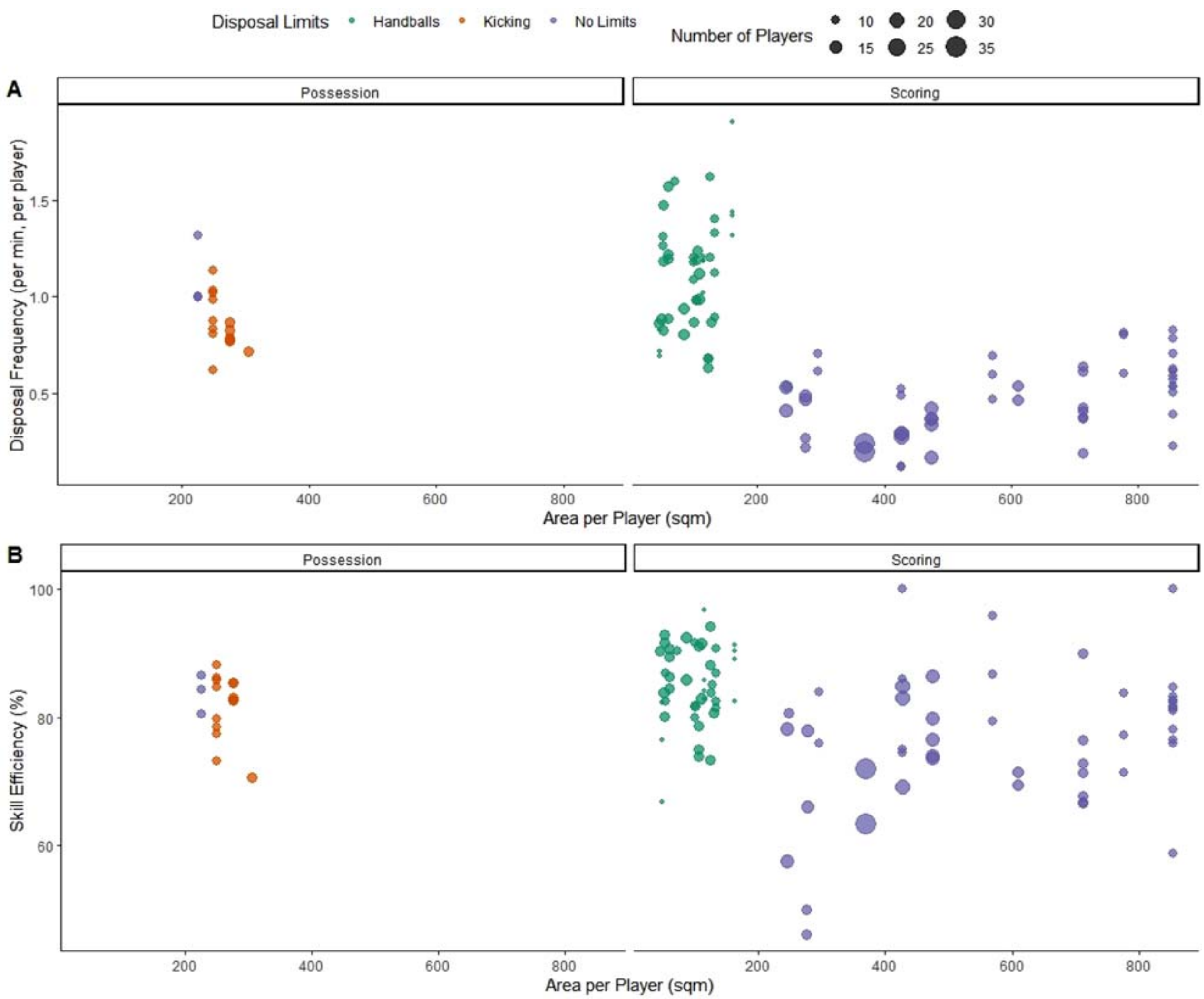

Figure 2. Relationship between manipulated environmental (area per player and number of players) and task (activity objective and disposal limitations) constraints and disposal frequency (A) and skill efficiency (B). Disposal frequency is reported as disposals, per min, per player and skill efficiency is reported as the number of effective involvements relative to total involvements (%). Each point represents a single training activity.

(Fleay et al., 2018) and other team-sports (Casamichana & Castellano, 2010; Kelly & Drust, 2009). However, area per player can influence other action frequencies not measured in the current study, such as tackles and interceptions (Casamichana & Castellano, 2010; Fleay et al., 2018; Kelly & Drust, 2009).

Table 2. Rulesets for the time in possession and pressure classification based on association models.

Model	Area per player (m^2)	Number of players	Team outnumber	Activity objective	Disposal limits	Constraint class	Support (%)	Confidence (%)
Time in possession	248–263	0–15	1–4.5	Possession	Kicking	<2 sec	9.9	95.4
	92.9–248	0–15	1–4.5	Possession	All disposals	<2 sec	3.5	84.4
	0–92.9	0–15	0–1	Scoring	Handballs	<2 sec	10.6	83.4
	263–276	0–15	1–4.5	Possession	Kicking	<2 sec	4.6	72.1
	92.9–248	0–15	0–1	Scoring	Handballs	<2 sec	14.9	62.5
	276–590	15-Inf	0–1	Scoring	All disposals	>2 sec	8.8	60.3
						<2 sec	65.8	65.8
Pressure	235–263	9-Inf	0–4.5	Possession	Kicking	None	8.7	84.1
	523-Inf	9-Inf	0–4.5	Scoring	All disposals	None	13.1	76.4
	131–235	9-Inf	0–4.5	Scoring	Handballs	Pressure	3.1	75.8
	276–451	9-Inf	0–4.5	Scoring	All disposals	None	8.7	73.6
						Pressure	42.4	42.4

The time in possession and pressure class is predicted based on the five associated manipulated constraints with support and confidence provided for each rule. Rules are ordered by confidence with a default rule provided for each model.

Activities with a scoring objective, limited to kicking only or which permitted all disposals, were most associated with decreasing the mean disposal frequency per player. Accordingly, permitting kicks to occur within a drill, in addition or exclusion to handballs, decreased disposal frequency. Execution of the kicking action takes longer than the handball, however this result may also be partially explained by the rules of AF. In AF, catching a kicked pass over 15 m (a "mark") results in a stoppage of play which acts as a task constraint on behaviour. When kicking is permitted, players may be exploiting this task constraint to afford themselves additional time for decision making. This behaviour slows the play of the drill, reducing the volume of disposals accrued. AF practitioners may want to consider this when determining the length of time for activities to provide players enough time to accrue desired action opportunities. More generally, it is advised that sport practitioners consider how task constraints may increase or decrease the frequency of action opportunities provided to their athletes.

Manipulating the number of players in the drill was also shown to influence disposal frequency, albeit to a lesser extent than disposal limitations or drill objective. This result is similar to research in field hockey (Timmerman et al., 2019), but dissimilar to other work in AF (Bonney et al., 2020). Results from the present study may be due to the larger manipulations of playing number. Importantly, reducing playing number increases opportunities for players to explore possible movement solutions (Davids, Araújo, Correia, & Vilar, 2013), while offering a simple and effective constraint manipulation available for coaches.

Modelling of skill efficiency was not as accurate as for disposal frequency, explaining only 26% of the variation. Similar results were observed when modelling rugby place kick performance during match play, explaining 28% variance (Pocock et al., 2018). Additional, or alternative, constraints may be required to predict skill efficiency more accurately. Skill efficiency, or relative frequency of skill errors, may be indicative of how challenging a training drill is for players (Farrow & Robertson, 2017). This is an important consideration for training design as an appropriately challenging environment may promote exploration for new movement solutions (Davids et al., 2013; Renshaw et al., 2010). It should be noted that the 2019 competition average disposal efficiency was 71.5% (obtained from https://www.afl.com.au/stats) compared to 80.9% in the present study. This may mean that the constraints manipulated during training presented a less challenging environment to players.

In the present study, activities which permitted all disposals or were limited to kicking only were most associated with reducing skill efficiency. This may indicate that kicking was a more difficult skill to execute than handballing. Similarly, in soccer, the success of passes and interceptions during small side games has been influenced by manipulating the task constraint of scoring mode (Almeida et al., 2016). Manipulating the team outnumber or area per player did not influence skill efficiency in the present study, which conflicts with other small sided game research in AF (Bonney et al., 2020) and field hockey (Timmerman, Farrow, & Savelsbergh, 2017). These results may be explained by the higher skill level of the current study's participants who can express greater skill proficiency adapted across a variety of conditions.

A multivariate analysis is more appropriate for understanding skilled behaviour (Browne et al., 2019; Robertson et al., 2019). In the present study, a Classification Based on Association approach determined the interactions between manipulated task and environmental constraints and their influence on the possession time and pressure on skill involvements. The variable rulesets, and associated confidence levels produced in the two models demonstrate the non-linearity of environmental and task constraint interaction during training. The complexity of constraint interaction is similarly exemplified during match play in other AF work (Browne et al., 2019, 2020). It is suggested that coaches seeking to apply principles of the constraints-led approach should measure and analyse constraint manipulations in a multivariate manner to appropriately contextualise player behaviour during training. Capturing detail in this way can provide further insight into *how* and *why* certain behaviours emerge (Glazier, 2017).

Each rule presented in the models demonstrate the adaptive behaviour of players within training activities. Accordingly, this highlights how practitioners can facilitate skill development through the design of training environments (Woods et al., 2020). Practically, Classification Based on Association can be utilised to assist coaches in achieving this by informing training design. For example, a coach may seek to develop player skill by increasing the temporal demands on players when passing. The rules presented in the possession time classifier (Table 2) can inform the coach of the relevant constraint manipulations which achieve this. For example, the top row of Table 2 shows the set of constraint manipulations which maximise the frequency of skill involvements with <2 s possession time (95%). Thus, using Classification Based on Association, a practitioner could evaluate the behaviour of players within training activities and use this to inform future drill prescription.

Neither classification model was able to substantially improve, upon the majority class threshold, the accuracy of predicting time in possession or pressure. Accordingly, this indicates that many of the activities in the dataset did not constrain participants to a high frequency of skill involvements in a single class of time in possession or pressure. This demonstrates the inherent variability of AF small side games which can promote movement performance in a range of contexts (Davids et al., 2013). These results may be an example of training which encourages athletes to explore different movement solutions to achieve tasks (Chow, 2013). Thus, evaluating the accuracy of predictive models may help practitioners measure the functional variability in training, where low prediction capability is not always viewed as a negative outcome.

Importantly, it should be noted that the proportion of constraint classes and manipulations across the dataset are representative of the participant coaching and playing styles. Team strategy and coaching philosophies will likely influence the focus of training sessions, guiding the design and selection of training activities. Results of the current study are population specific and practitioners are encouraged to utilise a similar methodology, as presented here, to inform their own training. Through a multivariate analysis, such as Classification Based on Association, practitioners can further contextualise their athlete's behaviour, evaluating and informing their own constraint manipulations in the field.

Given the applied nature of this study, there were some limitations which should be stated. Skill involvement data were collected in the field where constraint manipulation was not systematic but designed by coaches as desired for any given session. The representation of some constraint manipulations and constraint classes in the dataset are unequal, potentially influencing some results. Future work should be directed to collecting additional constraints to include in analyses to aide in constructing more sophisticated models. Environmental constraints such as weather or performer constraints such as age or playing experience may play an important role in influencing skilled behaviour during training. The inclusion of coach experiential knowledge is recommended to identify these key constraints (Greenwood, Davids, & Renshaw, 2012; Pocock, Bezodis, Wadey, & North, 2020).

Conclusion

This study examined the relationship between environmental and task constraint manipulations with skilled behaviour in elite AF. Constraint manipulations explained more variance in disposal frequency than skill efficiency. Designing activities that have a scoring objective and permitted kicking tended to reduce the disposal frequency of players. Designing activities which permitted any disposal method were most associated with a decrease in skill efficiency, creating a more challenging environment for players. A Classification Based on Association approach highlighted the variability of training activities and demonstrated how multivariate analysis can be used to determine constraint interaction, including influencing possession time and pressure on skill involvements. To enhance athlete skill development, practitioners are encouraged to measure interacting constraint manipulations, using similar multivariate analysis, to evaluate and inform their own training design.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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