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

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Abstract

An important consideration for sport practitioners is the design of training environments that facilitate skill learning. This study presented a method to determine individual (age, games played, height, mass, and position), environmental (activity type) and task (pressure and possession time) constraint interaction to evaluate player training behaviour. Skill actions (n=7301) were recorded during training activities (n=209) at a single professional Australian Football club and four measures of player behaviour were determined for each activity: disposal frequency, kick percentage, pressure, and possession time. K-means clustering assigned training activities into four groups, with regression trees used to determine the interaction between constraints and their influence on disposal frequency and type. For most regression tree models, only the environmental constraint was included. This showed all players adapted similarly to the constraints of each training activity. In one exception, a critical value of 60 games experience was identified as an individual constraint which interacted with activity type one to influence disposal frequency. Practically, this individual constraint value could be used to guide training design by grouping players of similar experience together. This study is presented as a practical tool for sport practitioners and coaches, which considers constraint interaction, to evaluate player behaviour and inform training design.

Keywords

Small side games, team sport, coaching, skill acquisition, performance analysis, training design

Introduction

An important consideration for sport practitioners relates to the design of training environments that can facilitate skill learning (Davids, 2012). Training, then, is an important component of the coaching process, especially in high performance sport (Hodges & Franks, 2002; Orth et al., 2019). Moreover, it is the design of game-like training tasks that are particularly important to support the development of an athlete's skill (Chow, 2013; Davids et al., 2008). What makes training design challenging, is that skill is an emergent phenomena that results from the various interactions of the person (i.e., the athlete), the environment they perform in, and the task they are undertaking (Araújo et al., 2006; Newell, 1986). In other words, it is a confluence of interacting constraints that shapes the emergence of skill, and the goal of the coach in training design, then, is to nudge or guide athletes towards useful movement and performance solutions (Woods et al., 2020).

The constraints-led approach (CLA) is a framework that can be used to help practitioners with the design of practice tasks (Davids et al., 2008; Renshaw et al., 2010). In this framework, constraints are understood as boundaries, which exist along multiple time-scales, that shape the emergent actions of individuals (Newell, 1986; Newell et al., 2001). Broadly, constraints are classified into one of three classes: task, environmental and individual (Newell, 1986). In sport, task constraints typically relate to the intent of an activity; what needs to be achieved and within what time. Environmental constraints include features external to the performer, such as ambient weather conditions, ground surface properties, and field size. Individual constraints pertain to characteristics of a performer, like anthropometric and physiological qualities, or emotional states and arousal levels.

In harnessing tenets of the CLA, practitioners can guide athlete behaviour through the careful manipulation of constraints in practice tasks (Renshaw et al., 2010; Renshaw & Chow, 2019). For example, reducing field size can increase the frequency of interceptions in soccer (Casamichana & Castellano, 2010), or manipulating a team outnumber can increase the frequency of passes to uncovered players in Australian Football[1] (Bonney et al., 2020). The manipulation of key constraints encourages

[1] Australian Football is an invasion team sport consisting of 22 (18 on field and 4 substitutes) players per team during match play where teams compete to score points by kicking goals (6 points) or behinds (1 point). In

problem-solving and facilitates an athlete's exploration for movement solutions (Woods et al., 2020). Thus, to assist with athlete learning, the evaluation of constraint manipulations, and how they have shaped emergent behaviour, can be of use for sports practitioners (Teune, Woods, et al., 2021).

A challenge for practitioners in evaluating athlete behaviour is that constraints do not function in isolation but interact, often non-linearly (Newell, 1985). Accordingly, constraint interaction is important to consider, to protect against the influence of a constraint being over or under valued when contextualised within larger constraint sets. This increases the complexity of implementing constraint manipulations during practice and understanding their combined influence on behaviour. In field hockey, for example, the number of players (i.e., an environmental constraint) and the intent of the task, have been shown to interact, influencing the frequency of certain actions (Timmerman et al., 2019). Moreover, studies in Australian Football have examined the multivariate interaction between task and environmental constraints to evaluate match play kicking performance (Browne et al., 2019; Robertson et al., 2019), goal kicking performance (Browne et al., 2022) and skilled behaviour during training activities (Teune, Woods, et al., 2021). Together, this work demonstrates how considering the interaction of multiple constraints may garner more precise insights to support practice design. However, investigations of constraint interactions have mainly been limited to environmental and task constraint classes. To build upon this work, studies which include individual constraint interactions with environmental and task constraints are largely yet to be explored. One exception in Rugby Union modelled place kicking effectiveness using logistic regression including interaction between game time (environmental constraints), score margin (environmental constraint), previous kick success (individual constraint), distance (task constraint) and angle (task constraint) to goal (Pocock et al., 2018). In this study, distance and angle to goal were found as significant variables included in a model that accurately classified 76% of kick outcomes. With this approach, threshold values which influenced kick success for distance and angle to goal were identified, information that could guide place kicking practice design.

Australian Football, players are permitted to pass the ball via kicking or handballing (punching the ball with a closed fist). Furthermore, players may be allocated specific roles within a team however, roles are dynamic and not restricted by any rules (Australian Football League, 2021)

Multivariate analytical techniques, which can consider non-linear constraint interaction, are important to appropriately contextualise player behaviour (Browne et al., 2021). Some analytical techniques, such as rule induction or decision trees, have such capabilities and have been applied to constraint analysis in Australian Football competition (Browne et al., 2019, 2022; Robertson et al., 2019) and practice (Browne et al., 2020; Teune, Woods, et al., 2021). Further, unsupervised machine learning techniques such as *k*-means clustering algorithms have been applied to Australian Football to group training activities according to similarities in player performance (Corbett et al., 2018). Specifically, *k*-means clustering has been useful to identify associations between training activity design and player performance (Corbett et al., 2018). These techniques provide interpretable outputs that make them applicable for end users in sport, such as skill acquisition specialists or coaches. An adaptation of such techniques may be beneficial as a practical tool for such practitioners to evaluate team sport training while considering constraint interaction between all three classes. Therefore, the primary aim of this study was to present a method to measure the relationship between interacting task, environmental and individual constraints on skill involvement frequency and kick percentage during Australian Football training. A secondary aim was to highlight the value of determining constraint interaction in applied sport training environments.

Methods

Participants

Participants were listed Australian Football League players (n = 54, height = 187cm ± 7.83, mass = 84.7 kg ± 7.73, age = 24.4 years ± 3.42) at a single club during the 2021-2022 seasons. All participants provided written informed consent and were injury free at the time of participation. Ethical approval was obtained from the University Ethics Committee (application number: HRE20-138).

Data Collection

Data were collected on 209 training activities, consisting of 34 different activity designs. All activities were characterised as a small-sided game, where two teams competed against each other within a specified field of play. Each activity type varied in the task goals, rules, field size or number of players.

Skill involvement data were collected via filming with a 25 Hz two-dimensional camera (Canon XA25/Canon XA20) from a side-on or behind-the-goals perspective. Skill involvements during each activity were coded via notational analysis software (Sportscode, version 12.2.10, Hudl) using a customised code window whereby each skill involvement (or “disposal”) was labelled according to the type (kick or handball) and the player’s name who performed the skill (n = 7301). Each disposal was further labelled with two task constraints: pressure (present or absent) and possession time (<2 s or >2 s), which has been the approach used in other Australian Football work (Browne et al., 2020). Pressure was defined as a disposal performed within 3 m of an opponent, while possession time was defined as the time between receiving and disposing the ball. Inter-rater reliability of the notational coding was assessed using a hold-out sample of 168 disposals, not included in the main analysis, resulting in a Kappa statistic (Landis & Koch, 1977) of “almost perfect” (>0.8) for all variables. Intra-rater reliability was conducted after a 14-day washout period resulting in Kappa statistics ranging from “substantial” (0.67-0.8) to “almost perfect” (>0.8) across three coders.

Individual constraints for each player were recorded at the beginning of each season, which were height (cm), weight (kg), number of games played (#) and playing position (defender, midfielder, forward or key position). Key position players typically consist of tall forwards and tall defenders (McIntosh et al., 2021). Age (years) was also determined as the time period between the player’s date of birth and the date of training activity occurrence. Playing positions were assigned in consultation with the club’s coaching staff who were familiar with individual player roles. Distributions of each individual constraint are shown in Figure 1. Skill involvement data was labelled with individual constraints according to the player’s name associated with each disposal. For every training activity, each player’s skilled performance was then summarised according to four measures: disposal frequency, kick percentage, pressure, and possession time. These measures were chosen through consultation with club’s coaching staff and Australian Football literature (Teune, Woods, et al., 2021). Disposal frequency was calculated as the total disposals divided by the activity duration in minutes, while kick percentage was represented as the percentage of kicked disposals. Pressure was represented as the percentage of pressured disposals, and possession time was represented as the percentage of disposals <2 s. These calculations resulted in 2499 individual training activity performances.

FIGURE 1 ABOUT HERE

Figure 1. Distribution of each individual constraint included in analysis.

Statistical Analysis

To determine the influence of constraint classes and their interactions on player skilled behaviour, four analyses were conducted. This approach was taken to demonstrate the influence of constraint classes when considered both in isolation and in combination.

In the first analysis, regression trees were used to estimate the interaction between constraints (Morgan et al., 2013). To determine the influence of individual constraints alone on player performance, two regression trees were grown, estimating disposal frequency and kick proportion, respectively. To determine the interaction between individual and task constraints, two further regression trees were grown to estimate pressure and possession time. All statistical analysis occurred in the R programming environment (R Core Team, 2019), with regression trees grown using the *rpart* package (Therneau & Atkinson, 2022). The five individual constraints were included as predictors in each of the models, and parameters were specified with a minimum split of 20 observations and a complexity parameter of 0.01.

In the second analysis, *k*-means clustering was used to identify the training activities which result in similar player outputs and were grouped accordingly to determine the influence of environmental constraints on skilled behaviour (Corbett et al., 2018). A scree plot was first generated to determine the appropriate number of clusters to use in analysis. 10 maximum iterations were permitted, with each training activity then assigned to one of the cluster memberships according to the results of the *k*-means clustering.

In the third analysis, to determine the interaction between environmental and individual constraint classes on skilled behaviour, regression trees were grown to estimate disposal frequency and kick percentage. Each of the five individual constraints and the environmental constraint of activity type were included in the two models using the same parameters as previous models.

In the fourth analysis, to determine the interaction between environmental, individual and task constraint classes, two regression trees were grown to estimate pressure and possession time. The five individual constraints and the environmental constraint of activity type were included as predictors in the model. The same model parameters were used as previous models.

Results

Across 2499 training activities, the mean and standard deviation was 0.59 ± 0.46 disposals per minute, 60.2% ± 40% kicks, 40.7% ± 39.5% pressured disposals, and 51.2% ± 40% disposals <2 s. For the two regression tree models which included only individual constraints, the first estimated disposal frequency with a mean squared error of 0.22 disposals / min. The second model estimating kick percentage had a root mean squared error of 44.02 %. For the two regression trees which estimated task constraints using only individual constraints as predictors, the model estimating pressure had a root mean squared error of 39.49 %. The model estimating possession time had a root mean squared error of 39.98 %.

Visual analysis of the scree plot resulted in four clusters being selected. The four cluster centres resulting from the subsequent *k*-means clustering analysis is shown in Table 1. The distributions of the player performance metrics (disposal frequency, kick proportion, pressure, and possession time) within each activity membership are shown in Figure 2. Cluster one was distinguished as handball only activities, with high levels of disposal frequency, pressure and lower possession times. Cluster two had the highest proportion of kicked disposals and disposals <2 s and the lowest level of pressure. Cluster three had the lowest disposal frequency, a high proportion of kicks with low pressure and time constraints. While cluster four was similar to cluster one in terms of pressure and possession time, it involved predominantly kicked disposals with a lower disposal frequency.

Table 1. Cluster centres (averages) of each training performance metric for drill activity memberships

Cluster membership	Disposal Frequency (p/min)	% Kicked Disposals	% Pressured Disposals	% Disposals <2 s
1	1.11	0	61.6	66.0
2	0.69	82.0	21.3	79.4
3	0.39	78.5	28.3	33.8
4	0.45	69.5	76.2	53.0

FIGURE 2 ABOUT HERE

Figure 2. Distribution of training performance metrics; disposal frequency **(A)**, kick percentage **(B)**, pressure **(C)** and possession time **(D)** within each activity membership. Note, in panel **B**, data for cluster membership one has not been displayed given that no kicked disposals were recorded in this membership.

The regression trees that included environmental and individual constraints, estimating disposal frequency and kick percentage, are shown in Figures 3 and 4, respectively. The results of the tree estimating disposal frequency had a mean squared error of 0.129 disposals / min and an R squared value 0.40. Games played was the only individual constraint included in the model which was shown to positively influence disposal frequency for activities in membership one. The regression tree estimating kick percentage had a root mean squared error of 29.83 % and an R squared value of 0.54. No individual constraints were included in this model.

FIGURE 3 ABOUT HERE

Figure 3. Regression tree modelling disposal frequency (disposals / min). Environmental constraints (cluster memberships) and individual constraints (age, games played, height, mass, position) were included as independent variables. The top number reported in each node represents the estimated outcome value (disposals / min). The bottom values in each node represent the frequency and percentage of cases within each node.

FIGURE 4 ABOUT HERE

Figure 4. Regression tree modelling disposal type (% of kicked disposals). Environmental constraints (cluster memberships) and individual constraints (age, games played, height, mass, position) were included as independent variables. The top number reported in each node represents the estimated outcome value (% of kicked disposals). The bottom values in each node represent the frequency and percentage of cases within each node.

The regression trees that included environmental and individual constraints, used to estimate task constraints, pressure and possession time, are shown in Figures 5 and 6, respectively. The results of the model estimating pressure had a root mean squared error of 34.69 % and an R squared value of 0.22. The model estimating possession time had a root mean squared error of 35.62 % and an R squared value of 0.21. Neither of these models included any individual constraints to partition the data.

FIGURE 5 ABOUT HERE

Figure 5. Regression tree modelling pressure (% of pressured disposals). Environmental constraints (cluster memberships) and individual constraints (age, games played, height, mass, position) were included as independent variables. The top number reported in each node represents the estimated outcome value (% of pressured disposals). The bottom values in each node represent the frequency and percentage of cases within each node.

FIGURE 6 ABOUT HERE

Figure 6. Regression tree modelling possession time (% of disposals <2s). Environmental constraints (cluster memberships) and individual constraints (age, games played, height, mass, position) were included as independent variables. The top number reported in each node represents the estimated outcome value (% of disposals <2s). The bottom values in each node represent the frequency and percentage of cases within each node.

Discussion

This study demonstrated a method to evaluate player performance in a team sport training environment by considering the interaction of individual, environmental and task constraints. Results showed that the environmental constraint of activity type was the most influential on player performance, indicating that players adapted their performance to suit the training activity design. The individual constraints collected in this study had limited influence on player performance, suggesting that coaches achieved activity designs that constrained player behaviour in a similar way, regardless of individual characteristics. In one exception however, games played showed an interaction with activity type one, suggesting that experienced players were able to perform more disposals than less experienced teammates. Task and environmental constraint interaction was also noted, indicating the environmental constraint of activity type influenced the levels of the task constraints, pressure and possession time, however, the individual constraints collected in this study did not influence this.

Individual constraints, when considered alone, did not influence disposal frequency or kick percentage, nor did they influence the task constraints of pressure or possession time. This contradicts other work where individual constraints have been influential on skilled performance (Almeida et al., 2016; Cordovil et al., 2009; Pocock et al., 2018, 2021). This result may be explained by the wide range of varying activity types included in the current study, leading to variability in performance. Individual constraints are perceived by coaches as an important feature to consider in practice design (Pocock et al., 2020). However, these results indicate that there were no general trends in player performance which were applicable across all activity types. Further context to these constraints is required, thereby helping coaches evaluate player performance more effectively. This result may also mean that different or more sensitive individual constraints need to be considered in future research, inclusive of physiological qualities, such as heart rate, or psychological attributes, such as confidence level (Pocock et al., 2021).

The *k*-means clustering was beneficial to determine associations between the practitioner's activity designs and player performance, whereby activities resulting in similar player performances could be grouped. For example, the activities included in cluster one were limited to handballs only – representing tasks with a rule constraint that did not permit kicking. Contrastingly, cluster two activities were designed with constraints which encouraged a high proportion of quick kicks with low levels of pressure. This suggests, within this group of activities, that players were able to identify passing options quickly and dispose of the ball before defensive pressure could be applied. *K*-means clustering could be helpful for activity prescription, allowing coaches to select a range of activities from particular groups which meet certain training targets, such as a focus on kicking or performing disposals under pressure. Accordingly, relevant support staff, such as data analysts or skill acquisition specialists, may use such analysis to help guide the design of practice tasks through careful manipulation of constraints (Woods et al., 2020). Additionally, the clustering approach used here is flexible, meaning it can be applied to any team and across any parameters deemed important by practitioners.

Including the environmental constraint of activity type with individual constraints in the regression trees improved the model's accuracy. This result was expected, as activity type was previously grouped according to the player performance metrics. However, the individual constraints included in the models had limited capacity in explaining further variance within each activity type. This result highlights the capability of the coaches to design activities that constrain player performance similarly. Thus, the minimal influence of individual constraints is a beneficial insight for practitioners, identifying the consistent influence of their activity design across all players, regardless of individual characteristics. In one exception, an interaction between activity type one and games played influenced disposal frequency. According to the cluster centres, activity type one was characterised as a fast game with high disposal frequency using only handballs, high levels of pressure, and high levels of temporal constraints. Accordingly, within this group of activities, experience was important in shaping how often a player performed a disposal (Baker et al., 2003). This may be due to the higher skill of experienced players to perform under increased temporal and spatial constraints, positioning themselves more optimally to receive and dispose the ball. Alternatively, experienced players may be more frequently sought out by teammates as passing options.

Importantly, within activity type one, the regression tree model identified a critical value for experience of 60 games, which may be leveraged by coaches to inform individual differences in performance during this activity type. Though, it may be beneficial for coaches to utilise support from a broader staff team, including a skill acquisition specialist, to best glean such information. Indeed, the benefits of skill acquisition support has been highlighted in (para-) Olympic sports (Pinder & Renshaw, 2019; Williams & Ford, 2009). Thus, a skill acquisition specialist (perhaps working closely with performance analysts) could undertake an analysis such as that described here, to then be reported back to coaching staff as additional information which may guide how constraints can be manipulated during practice tasks. For example, in the present study, players could be divided into "more experienced" (> 60 games) and "less experienced" (< 60 games) groups. Coaches may utilise this grouping to achieve their training goals, purposefully accelerating the skill development of less experienced players by placing them against more experienced ones. Alternatively, less experienced players may train against other less experienced players, potentially increasing their disposal frequency and providing them with more learning opportunities. Less experienced players could also be provided additional training activities after the session, or the activity could be run for longer to allow these players to accrue more disposals. Regardless, this result exemplifies how the analysis can be practically implemented by skill acquisition specialists and performance analysts to assist a coach's ability to structure and plan training sessions that consider individual differences (Chow, 2013).

The environmental constraint of activity type interacted with the two task constraints of pressure and possession time however, the regression trees were only able to explain 22% and 21% of the variance in these constraints, respectively. This indicated that these constraints were highly variable within activity types and may be a result of constraint manipulations implemented by coaches which were not collected in this study. For example, field dimension or the number of players may have been manipulated from session to session, according to changes in player availability or to directly influence player performance. Indeed, field dimension and the number of players has been shown to influence player performance in Australian Football (Bonney et al., 2020; Fleay et al., 2018; Teune, Spencer, et al., 2021; Teune, Woods, et al., 2021). In the present study, only the environmental constraint of activity type was shown to influence the task constraints, with none of the individual constraints included in the resulting models. Accordingly, alternate or improved measures of individual constraints may need to be collected to determine their influence on player performance. For example, players were allocated into one of four positions; forward, midfield, defender or key position. However, unlike some sports, such as netball, the nature of positions in Australian Football is dynamic. More detailed position groupings may influence the models such as including small general forwards and defenders, or rucks, as used in other Australian Football work (McIntosh et al., 2018).

Given the applied nature of the current study, there are limitations that require acknowledgement. First, specific constraints such as field dimensions, number of players or task rules were not collected. This could have been manipulated by coaches between sessions and may therefore have influenced behaviour. These environmental and task constraints have been modelled in previous Australian Football work (Teune, Woods, et al., 2021), however, future studies may look to include individual constraints within such models to provide deeper insight into player behaviour. Additionally, environmental constraints, like fluctuations in wind, rain, ambient temperature or time in session of the practice task were not collected, which may have influenced player performance. Future work may also measure a broader range of player behaviour metrics within training activities, including defensive skill involvements, such as tackles or intercepts, skill involvement effectiveness, or team behaviour metrics such as team separateness or surface area. Finally, given the broad time range in which data collection occurred, it is possible that player performance changed according to tactical directions of coaching staff. Thus, future work may benefit from measuring training performance adaptations over longitudinal timelines to inform training design (Farrow & Robertson, 2017).

Conclusion

This study developed a method to measure interaction between individual, environmental and task constraints during Australian Football training. The environmental constraint of activity type was the most influential on individual training performance, highlighting the achievement of coaches to design training which constrains all players similarly. The individual constraint of player experience interacted with one activity type. It was shown how the analysis can be used to identify critical constraint values, such as 60 games played, which can inform training design by allocating players into specific groupings. This study is presented as a practical tool for sport practitioners and coaches to evaluate the performance of their players during training and inform the design and structure of training activities.

List of abbreviations

CLA Constraints Led Approach

Declarations

Competing interests

The authors declare that they have no competing interests.

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