

## How performance analysis of elite long jumping can inform representative training design through identification of key constraints on competitive behaviours

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1	How performance analysis of elite long jumping can inform representative training
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## 24 Abstract

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Analysing performance in competitive environments enables identification of key constraints which shape behaviours, supporting designs of more representative training and learning environments. In this study, competitive performance of 244 elite level jumpers (male and female) was analysed to identify the impact of candidate individual, environmental and task constraints on performance outcomes. Findings suggested that key constraints shaping behaviours in long jumping were related to: individuals (e.g., particularly intended performance goals of athletes and their impact on future jump performance); performance environments (e.g., strength and direction of wind) and tasks (e.g., requirement for front foot to be behind foul line at take-off board to avoid a foul jump). Results revealed the interconnectedness of competitive performance, highlighting that each jump should not be viewed as a behaviour in isolation, but rather as part of a complex system of connected performance events which contribute to achievement of competitive outcomes. These findings highlight the potential nature of the contribution of performance analysis in competitive performance contexts. They suggest how practitioners could design better training tasks, based on key ecological constraints of competition, to provide athletes with opportunities to explore and exploit functional intentions and movement solutions high in contextual specificity.

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- Keywords: Performance analysis, long jump, representative learning design,
- 45 ecological dynamics, interacting constraints

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Performance analysis in sport competition provides a quantitative link between application, science and theory through an objective audit of athlete or team behaviours (Hughes & Bartlett, 2002; McGarry, 2009). Performance is traditionally described through evidence gained from notational analysis using competition, technical and tactical indicators, as well as biomechanical technique descriptors using kinematic and kinetic variables. In sports like track and field, performance analysis has predominantly taken the form of movement analysis. For example, in long jump, most analyses have been driven by biomechanical (e.g., Bridgett & Linthorne, 2006; Hay, 1993) and motor control research (e.g., Glize & Laurent, 1997; Montagne, Glize, Cornus, Quaine, & Laurent, 2000) in controlled, experimental or training environments (for an exception see Hay, 1988). Whilst these studies have increased understanding of performance variables, insufficient attention has been paid to analysing how long jump performance under the specific constraints of competition environments might impact self-regulation in athletes. Performance analysis, investigating competition behaviours, could enrich understanding of self-regulatory interactions of athletes with the environment during practice, revealing links between strategies, psychological states, emotions and actions in individual athletes (Anderson, 2018; Hughes & Bartlett, 2002).

With a large range of variables available to analyse during long jump competition performance, it is important that selection and interpretation of data are guided by an appropriate theoretical framework. One proposed framework is ecological dynamics which has enhanced the understanding of performance and

learning in a variety of sport contexts (Araújo, Davids, & Hristovski, 2006; Vilar, Araújo, Davids, & Button, 2012; Warren, 2006). Ecological dynamics proposes how human behaviour emerges through continuous interactions with affordances (opportunities for action) available during performance, as multiple constraints act on the (athlete-environment) system (Araújo et al., 2006; Araújo, Davids, & Passos, 2007; Gibson, 1979), providing rich information for self-regulation. Adopting this theoretical framework to guide the analysis and interpretation of performance in long jump, moves performance analysis beyond merely documenting discrete variables from isolated events within competition. Such an approach allows for the recognition of the conditioned coupling evident in dynamic performance environments where constraints are deeply intertwined to shape athlete performance (Vilar et al., 2012). Practically, identifying these constraints provide practitioners with the opportunity to enhance the development of representative training designs where intentions, perceptions and actions emerge in faithful simulations of a performer's actions in competition (Pinder, Davids, Renshaw, & Araújo, 2011). Current empirical research on how ecological dynamics can enrich performance analysis highlights the unique interactions of individual, environmental and task constraints that shape the emergence of athlete performance behaviours (Travassos, Duarte, Vilar, Davids, & Araújo, 2012; Vilar, Araújo, Davids, & Bar-Yam, 2013; Vilar et al., 2012). Previous research on personal constraints suggest that a key variable that shapes the perception-action couplings of athletes is specific intentions during performance. Athlete intentionality concerns the adoption of specific performance goals (i.e., winning a competition, making the podium, qualifying for a final, jumping conservatively to avoid a 'no-jump'), constrained by the particular needs, wishes and desires of an athlete at a particular point in time

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(Araújo, Davids, & Renshaw, 2018). To exemplify, intentions to make a 'safe' jump or a jump for maximal distance clearly influence running velocity and foot placement error on the take-off board (Bradshaw & Sparrow, 2000; Maraj, Allard, & Elliot, 1998). This practical example illustrates how athletes might deliberately adapt movement behaviours in order to complete a task in a *specific* way, related to current performance goals or competitive needs. The successful (or unsuccessful) execution of specific performance strategies is likely to impact future jump performance as the athlete adapts to his/her emerging needs in an unfolding competitive event, with interconnected performance trials. Each jump within a competition comprises a complex system, a series of connected events to influence overall competitive performance outcomes (Renshaw & Gorman, 2015). This complex system of competitive jumps can be perturbed by emerging cognitive-emotional-physical demands at a specific performance event (Headrick, Renshaw, Davids, Pinder, & Araújo, 2015).

Environmental constraints, including physical (i.e., wind, ambient light, temperature, altitude, air density) and social variables (i.e., family support, peer groups, an evaluating audience and cultural norms) can also influence athletic performance. In long jumping, the influence of wind speed and direction on jump performance is unique as stability of running and jump components can be perturbed during task execution. Mathematical modelling has suggested influences on long jump distance of between 0.08-0.12 m for a 1 m/s increase or decrease in wind velocity (de Mestre, 1991; Ward-Smith, 1985). The effects from drag during the aerial phase and running velocity during the approach run are primary causes of an increase in jump performance (Ward-Smith, 1985). The influence of wind on jump performance is compounded by sport regulations preventing a change in the

direction of an athlete's run-up if there is a change in weather conditions during competition (*Competition Rules 2014-2015*, 2013). This type of environmental constraint emphasises the importance of attunement to potential variability in performance conditions when preparing for competition by elite athletes.

Task constraints are more specific to performance contexts than environmental constraints (Davids, Button, & Bennett, 2008) and include the rules of a sport. In long jumping, the key rule is the requirement to keep the front foot behind the take-off line to register a legal jump, constraining run-up strategies. Research on the run-up approach in long jumping (e.g., Lee, Lishman, & Thomson, 1982; Montagne et al., 2000) has demonstrated that the presence of the take-off board, in comparison to jumping conditions with no take-off board, led to changes in foot placement throughout the entire run-up as well as lower levels of footfall variability (Maraj, 1999). The need to intercept an object or surface, such as a 20cm wide take-off board, when completing a task *nested* at the end of a run-up (i.e., jumping) has important implications for training design. Gait regulation strategies in run-ups with the absence of a nested jumping task show few similarities with performance in tasks requiring a jump at the end (Bradshaw & Aisbett, 2006; Glize & Laurent, 1997).

Identifying interacting constraints that shape exploration and utilisation of affordances (opportunities for action) in competition provides practitioners with a better understanding of the performance environment, thereby enhancing their capacity to design more effective practice tasks. Ecological dynamics proposes how training environments could be designed to provide athletes with opportunities to attune and calibrate their intentions, perceptions and actions in the landscape of affordances representative of competitive performance (Pinder et al., 2011). Such learning designs can enhance athlete adaptation to the dynamics of a competitive

performance environment, ready to self-regulate their behaviours as a competitive event unfolds. Currently, there is limited research investigating the constraints of competition in long jumping and there is a need for a more in-depth analysis of performance in elite long jump competitions. Consequently, this study aimed to investigate how performance analysis, under the framework of ecological dynamics, can lead to the identification of more contextual information for the design of practice environments. These sources of information could better reflect the intertwined interactions that emerge in between athlete intentions, perceptions and actions in adapting to changing event conditions. Elite level long jumping will be used as the exemplar, with key individual, environment and task constraints identified through the statistical analysis of elite long jump competitions held between 1999 and 2016. These competitions will include Olympic Games, World Championships and Diamond league competitions.

## Methods

Results from 108 (men = 56; women = 52) elite level long jump competitions were obtained from publicly available online databases (www.iaaf.org.au & www.diamondleague.com). These competitions included Diamond League competitions staged between 2011-2016 (men = 42; women = 39) and World Championship (men = 9; women = 8) and Olympic Game (men 5; women = 5) competitions between 1999-2016. These events covered a total of 244 athletes (male= 140; female=104) with 5 393 jumps (male = 2783; women = 2608) available for analysis. Two jumps under 2 m were excluded as outliers in the men's dataset as they were not reflective of a genuine attempt at a jump at that performance level.

Only performances of athletes in competitions where all wind (m/s) and horizontal jump distance (m) data were available, were included in the analysis.

Candidate variables that may potentially impact on performance were selected using an ecological dynamics rationale and the experiential knowledge of elite long jumping coaches identified in previous research (e.g., Greenwood, Davids, & Renshaw, 2012) (Table 1). For example, wind was selected as a candidate environmental variable, since mathematical modelling has suggested that a 1m/s increase or decrease in wind velocity has a 0.08-0.12 m impact on jump distance in long jump (de Mestre, 1991; Ward-Smith, 1985). The conceptualisation that each jump forms a part of a complex system, formed by a series of connected events (Renshaw & Gorman, 2015), supports the inclusion in the analysis of performance variables including previous round foul, round 1 foul, distance of round 1 jump, medal position after previous foul, top 8 previous round and previous round jump distance. It was predicted that these variables might impact the intentions or strategy implemented by athletes throughout a competitive event, and subsequent movement (re)organisation, depending on their competitive needs at a specific point in time (Bradshaw & Sparrow, 2000; Maraj et al., 1998).

#### Table 1 near here ####

To determine the effects of competition on jump distance, descriptive statistics were calculated for each competition type with median jump distance values compared using a Kruskal-Wallis test with a Bonferroni correction for multiple comparisons (p < .001). Effects of year of performance on jump distance was calculated using multiple linear regression (p < .001) and effects of round on jump distance was determined using analysis of variance. Post-hoc procedures

(Tukey's HSD) determined where differences existed if statistically significant differences were found.

To determine the variables that best predicted horizontal distance jumped, a linear mixed model with main effects, interactions and random intercepts was constructed. Univariate tests were first conducted to determine variables of significance. Variables tested for statistical significance appear in Table 1 (excluding 'Previous round jump distance'). These variables were explored in order of significance to determine the most parsimonious model explaining the most variability and were assessed using Aikake's Information Criterion (AIC). Two-way interactions only were considered for the purposes of the analysis. Statistical significance level was set at p = .05.

Descriptive statistics were calculated on jump classification (legal and foul jumps) with the effects of competition, round and time (years), on foul jumps made, determined using chi-square test for association and effect sizes. To determine variables which best predicted foul jumps, binary logistic regression was used. Variables included in the regression calculation were identical to those used in predicting jump distance with the addition of 'Previous round jump distance'.

#### Results

Table 2 provides descriptive statistics for jump distance and jump classification across all competitions for both men's and women's competitions. Multiple linear regression showed a statistically significant effect of the year of the competition (p < .001) with mean distance jumped decreasing by 1.2 cms per year for both men and women. The frequencies of foul jumps showed a significant annual effect in women's competitions only, but the effect size was small ( $\chi^2 = 25.6$ , p = .019, phi = 0.099).

Table 3 provides descriptive statistics of the effects of round on distance jumped and foul jumps recorded for male and female competitions. Analysis of variance demonstrated a significant effect of round (F (5, 1931) = 5.425, p = .003) on distance jumped for male competitions only. Post hoc testing indicated significant differences in distances jumped between Round 1 and 2 (p = .005), Round 1 and 3 (p = .008), Round 1 and 4 (p = .000) and Round 1 and 6 (p = .004). Overall, the number of foul jumps was significantly different between rounds ( $\chi^2$  = 17.9, p = .003) for female competitions only, with a small effect size (Phi = 0.083). For both men and women, total percentage of fouls was higher in the last three rounds (men: 31.49% & women: 32.45%), compared to the first three rounds (men: 29.66% & women: 26.85%).

#### Table 3 near here ####

Data on effects of competition on jump distance and classification for both male and female competitions are provided in Table 4. For men, median (non-normal distribution) jump distance for Diamond League (7.82 m) was significantly (p < .001) shorter than World Championship (7.99 cm) and Olympic Games (8.03 cm). In the female competitions, median distances (p < .001) and overall number of foul jumps were significantly different between competition types (Pearson Chi Square = 10.87, p = .004, Phi = 0.065).

#### Table 4 near here ####

In determining the best predictors of jump distance in male competitions, the main effects model showed a significant difference of competition type between Olympic Games and both Diamond Leagues and World Championships. Estimated marginal means revealed a larger statistical effect for Diamond Leagues with mean

jump distance value 16.8 cm (S.E. 0.64) less than that observed in Olympic Games with World Championships found to be 8.6 cm (S.E.0.70) less. Of the other variables, the largest effect on jump distance was found to be Round 1 jump distance (coefficient = 0.374). Effects of wind (1 m/s increase in tailwind or reduction in headwind) increased jump distance by 4.2 cm. In the interactions model, 'in medal position after last round' with competition type, was significantly different between the Olympic Games and Diamond Leagues (p = .006) only. Estimated marginal means suggested that a jump into a medal position increased the value of the subsequent round jump distance. Interactions of 'Distance of Round 1 jump' with competition type were also significantly different between the Olympic Games and the World Championships (p < .001).

For the women's competitions, a statistically significant difference was found between jump distance observed in Diamond Leagues and Olympic Games, with Diamond Leagues values being 12.8 cm shorter (S.E. 0.035) than Olympic Games, based on the estimated marginal means. Other variables found to be of significance in the main effects model were 'Round 1 jump distance' (coefficient = .219), 'Medal position after previous round' (coefficient = 0.113), and the effect of wind (5 cm increase in jump distance for 1 m/s increase in tailwind or reduction in headwind). No variables within the interactions model were significant.

In determining the best predictors of foul jumps, no factor or covariate was predictive of a foul jump in male competitions. Despite this observation, two factors in the current model appear to increase the odds of a given jump being a foul, albeit not statistically significantly. If a Round 1 jump was a foul, then the odds of the next jump being a foul increased by a factor of 1.67 - regardless of the round.

Additionally, if the previous jump had been a foul, the odds of the next jump

resulting in a foul, was 1.56 higher than if it had not been a foul. For female competitions, initial investigation showed that practically every factor measured was a significant predictor of foul jumps, but the final, most parsimonious model contained three terms: round, distance of first jump and previous jump being a foul. The odds of foul jumps (compared to round 1) are significantly increased in rounds 4 (OR 1.615) and round 5 (OR 1.530). For distance of first round jump, a unit increase (metre) in distance increased the odds of the next jump being a foul by a factor of 1.89. Thus, if an athlete made a first jump of 6.50 m, the odds of any remaining jump in the competition being a foul were increased by a factor of 1.89, compared to a competitor who made a first jump of 5.50 m. Furthermore, if an athlete recorded a foul in the previous round, then the odds of recording a second foul in succession were increased by a factor of 1.50.

## Discussion

In this study, we sought to identify how the analysis of competition data, framed by concepts from ecological dynamics, can provide a more nuanced understanding of long jump performance. This relationship between performance analysis and key tenets of the theory of ecological dynamics could assist practitioners in designing more effective training environments to reflect the intertwined interactions between intentions, perceptions and actions of athletes in performance. Analysis of competitive performance data of elite male and female long jumpers revealed that elite long jumping is defined by a mean jump distance of 7.81 m for men and 6.48 m for women. Interestingly, mean jump distance decreased by 1.2 cm per year for both men and women. In classifying jump outcomes, the percentage of jumps deemed fouls was 30.40% and 29.19%, respectively, for men

and women. The stagnation of long jump performance over time raises important questions, given advances in technology and sport sciences (e.g., Balague, Torrents, Hristovski, & Kelso, 2016; Pluijms, Canal-Bruland, Kats, & Savelsbergh, 2013) and potentially point to the need to carefully consider training designs to enhance performance.

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Findings revealed how continuous interactions of individual, task and environmental constraints influenced elite long jumping performance. The personal constraint of an athlete's (tactically defined) intentions continuously shape perception-action couplings during competition. It is these intentions, embedded within specific performances, that frame the interactions of athletes with task and environmental constraints to facilitate adaptive behaviours (Araújo et al., 2018). For example, the lowest value for mean jump distance and lowest percentage of fouls found in Round 1 suggests athlete intentionality on the first jump could be to record a 'safe' jump. Round 1 jumps were also significantly shorter than jumps in Rounds 2, 3, 4 and 6 in the men's competitions. The notions of a 'safe' jump could be interpreted as an athlete's deliberate adaptation of perception-action couplings (i.e., decrease in run-up velocity) to intentionally match his or her specific needs to the competition demands at specific points in time (Araújo et al., 2018; Maraj et al., 1998). The importance of the first round was also highlighted by its role in predicting jump distance and fouls in future rounds across the competition. This relationship between jump performances demonstrates that each jump is connected and forms an event (Gibson, 1979) influencing emergent jump performance (Renshaw & Gorman, 2015). The outcome of round 1 is, therefore, likely to impact the athlete's intentions in subsequent rounds, depending on the needs of the athlete at that particular point in the competition. Intentions, and hence perception-action

couplings, will be strongly influenced by an athlete's own goals, competitors' performances and ultimately the rules of the sport (only the top 8 athletes at the end of round 3, get three further jumps). For example, after a round 1 foul, an athlete may place more emphasis on making a 'safe' jump (i.e., speed/accuracy trade-off) in round 2 in order to increase the chances of making a legal jump that enables him/her to receive three additional jumps after round 3. This conceptualisation of emergent behaviours in long jump is an important development in better understanding performance as a series of complex interconnected events rather than seeing training as a series of isolated jumps, with important implications for training design.

The environmental constraint of wind was identified as a key influence on long jump competitive performance. A 1 m/s increase in tailwind (or decrease in headwind) increased jump distance for both women (by 5.0 cm) and men (by 4.2 cm). Previous research has attempted to determine the aerodynamic effects of wind on jump performance (de Mestre, 1991; Ward-Smith, 1985) using mathematical modelling. However, to date, no research has reported in-competition data. Evidence on the impact of wind as an environmental constraint on jump performance highlights the relevance of training designs which include experiences in variable wind conditions.

As expected, a major task constraint is rule-based: that a 'no jump' is recorded unless the take-off foot is behind the foul line. Satisfying this influential constraint shapes athletes' behaviours and actions in seeking to intercept the take-off board with the front foot. Foul jumps (at any time in a competition) were seen to increase the odds of subsequent fouls later in the competition. With almost a third (men: 30.40% and women: 29.19%) of jumps being classified as fouls, each athlete's tactical behaviours are influenced at any point in competition by these 'no' jumps.

For example, a foul jump in Round 1 increases pressure on an athlete to accurately hit the take-off board in Rounds 2 and 3, whilst also needing to jump for distance to qualify for the final three jumps. This increase in psychological and emotional demands, along with the known implications for run-up velocity and foot placement error on the take-off board when jumping for distance, defines how interactions between different constraints impact behaviour in elite long jump performance.

The findings of the current study have important implications for the design of representative training environments. Long jump coach education resources (e.g., Brown, 2013) typically fail to consider how competition behaviours can be invited through the design of training environments. Simulating conditions of competitive performance allows practitioners to model environmental and task constraints to shape intentions, perceptions and actions influencing performance in elite long jumping. Our analyses of elite competition revealed that the most influential interactions were between: athlete intentionality, effect of wind (direction and speed) and rules of the sport.

Identification of athlete intentions in the form of competition strategies highlights the need for training to focus on adaptations needed to achieve specific outcome goals, with athletes training in a series of connected jumps that replicate the demands of competition. This form of 'within-session periodisation' can be achieved by the creation of specific 'vignettes' for athletes, that seek to simulate the physical, emotional and psychological demands of competitive performance environments (Headrick et al., 2015). An exemplar scenario could focus on the context when an athlete has fouled in the first two rounds and must record a jump of sufficient distance in round 3 to qualify for a further three jumps. In this way, the reduction of emphasis on constant repetition in some practice sessions can have a functional value

of highlighting focus on a single performance trial, which simulates competition conditions. In this way practice task design could involve 'repetition without repetition' as advocated by Bernstein (1967), for example, challenging athletes to calibrate their actions (Van Der Kamp & Renshaw, 2015) to exploit variable wind speeds and direction. Asking athletes to complete the run-up and jump in variable wind speeds and direction during training will facilitate their attunement to variable weather conditions and adaptation of movement patterns accordingly. Exploitation of this environmental constraint in training will promote 'dexterity' (Bernstein, 1967) in athletes and simulate the level of uncertainty that exists in competitive performance. The high percentage of fouls across all competitions for both men and women, suggests that there may be a failure to give due emphasis to the importance of legal jumps in practice conditions (e.g., Brown, 2013). Whilst allowing fouls in training may increase trial repetition (practice volume) and reduce performance complexity, this approach fails to simulate the individual-environment relationships that performers forge in the competition environment (Davids & Araújo, 2010; Renshaw, Chow, Davids, & Hammond, 2010). Coaches need to recognise the take-off board as a key affordance that athletes must attune to in order to enable the development of functional perception-action couplings required in competition.

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## Conclusions

In summary, the theoretical framework of ecological dynamics suggests that a more nuanced understanding of the complexities of long jump performance could facilitate the design of more representative practice environments by practitioners.

We have considered how more contextual information from competitive

environments can enhance practice designs, following recent conceptualisation of the use of 'gold standard' data in understanding sports performance constraints (Anderson, 2018). Results from this study revealed three key constraints that shape performance behaviours in both male and female elite long jumping: (i) athlete intentionality, (ii) wind effects on run-up and jump phases, and (iii), adhering to rules of the sport. The integrated manipulation of these key constraints in training can provide opportunities for athletes to adapt to major physical and emotional demands of performance environments. The use of ecological dynamics to guide the analysis of competition data shows how performance analysis can be enhanced to enrich the understanding of athlete interactions during competition. Recognising the conditioned coupling evident in dynamic performance environments is a critical advancement in understanding movement behaviours in individual sports.

Our findings suggested the need to move beyond reductionist approaches to studying long jumping, currently provided by isolated biomechanical analysis of single jumping events (Mendoza, Nixdorf, Isele, & Gunther, 2009). Future work needs to embrace the complexity of competitive long jumping and adopt a more inter-disciplinary approach to performance analysis in context. Future research could also further our understanding of influential constraints on long jump performance through accessing the experiential knowledge of expert coaches and athletes.

Integrating experiential knowledge with theoretical concepts and research data would enhance understanding of interacting constraints impacting long jump performance. It would also provide a basis for analysing how key long jumping performance variables (such as in the run-up) may be shaped by competitive performance contexts. This integrated approach would reveal informational constraints that regulate athlete intentions, and perception-action couplings during

420 run-ups in sport tasks like long jumping, cricket bowling and gymnastics vaulting 421 (Greenwood, Davids, & Renshaw, 2014). 422 Disclosure Statement 423 No potential conflict of interest was reported by the authors. 424 Funding 425 The author(s) received no financial support for the research, authorship, and/or 426 publication of this article. 427 References 428 Anderson, E. (2018, 6-8 June). Representative movement behaviour measurement in 429 sport: Gold standard measurements versus gold standard data. Paper 430 presented at the Measuring Behaviour, Manchester, United Kingdom. 431 Araújo, D., Davids, K., & Hristovski, R. (2006). The ecological dynamics of 432 decision making in sport. Psychology of Sport and Exercise, 7, 653-676. 433 Araújo, D., Davids, K., & Passos, P. (2007). Ecological validity, representative 434 design, and correspondence between experimental task constraints and 435 behavioral setting: Comment on Rogers, Kadar, and Costall (2005). 436 Ecological Psychology, 19(1), 69-78. doi:10.1080/10407410709336951. 437 Araújo, D., Davids, K., & Renshaw, I. (2018). Cognition, emotion and action in 438 sport: An ecological dynamics perspective. In G. Tenenbaum & R. Eklund 439 (Eds.), *Handbook of Sport Psychology* (4th ed.). 440 Balague, N., Torrents, C., Hristovski, R., & Kelso, J. A. S. (2016). Sport science 441 intergration: An evolutionary synthesis. European Journal of Sport Science. 442 doi:10.1080/17461391.2016.1198422.

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# Table 1. Competition variables and definitions

Competition Variables	Constraint Classification	Definition				
Round	Task	Each competition consists of six rounds				
Wind	Environment	Measured in metres per second. Readings must be under 2 metres per second for jump to be valid for team selection and records				
Competition ID	Environment	Three competitions used for analysis (1) Diamond League or DL (2) World Championships or WC and (3) Olympic Games or OG				
Previous round foul	Individual	Previous round was classified as a foul				
Round 1 foul	Individual	Round 1 jump was classified as a foul				
Distance of round 1 jump	Individual	Round 1 jump distance measured in metres				
Medal position after previous round	Individual	Athlete enters round in either 1 <sup>st</sup> , 2 <sup>nd</sup> or 3 <sup>rd</sup> position				
Top 8 previous round	Individual	Athlete is in a Top 8 position entering the round. After the completion of Round 3, athletes in the top 8 positions are permitted 3 more jumps				
Previous round jump distance	Individual	Previous round jump distance measured in metres				

		Jump Distance		Jump Classification			
	Total jumps analysed	Mean (±S.D.)	Median (IQR)	Legal (%)	Foul (%)		
Male	2783	7.81 (±0.40)	7.88m (0.34)	1937 (69.90%)	846 (30.40%)		
Female	2607	6.48 (±0.35)	6.52 (0.33)	1846 (70.81%)	761 (29.19%)		

		Men's Con	npetitions		Women's Competitions				
Round	Total Jumps	Jump Distance (m)	Jump Classification		Total Jumps	Jump Distance (m)	Jump Classification		
	Analysed	Mean	Legal	Foul	Analysed	Mean	Legal	Foul	
		(±S.D.)	(%)	(%)		(±S.D.)	(%)	(%)	
1	559	7.73	406	153	509	6.45	381	128	
		$(\pm \ 0.44)$	(72.63%)	(27.37%)		$(\pm 0.33)$	(74.85%)	(25.15%)	
2	557	7.83	378	179	506	6.49	355	151	
		$(\pm \ 0.37)$	(67.86%)	(32.14%)		$(\pm 0.30)$	(70.16%)	(29.84%)	
3	543	7.83	383	160	501	6.47	373	128	
		$(\pm \ 0.39)$	(70.53%)	(29.47%)		$(\pm 0.35)$	(74.45%)	(25.55%)	
4	380	7.87	269	111	374	6.50	247	127	
		$(\pm \ 0.35)$	(70.79%)	(29.21%)		$(\pm 0.34)$	(66.04%)	(33.96%)	
5	369	7.82	252	117	361	6.49	234	127	
		$(\pm \ 0.46)$	(68.29%)	(31.71%)		$(\pm 0.41)$	(64.82%)	(35.18%)	
6	375	7.85	249	126	356	6.49	256	100	
		$(\pm 0.41)$	(66.40%)	(33.60%)		$(\pm 0.39)$	(71.91%)	(28.09%)	

Competition	Men's Competitions					Women's Competitions				
	Total Jumps Analysed	Jump Distance (m)		Jump Classification		Total	Jump Distance (m)		Jump Classification	
		Mean (±S.D.)	Median	Legal (%)	Foul (%)	Jumps Analysed	Mean (±S.D.)	Median	Legal (%)	Foul (%)
Diamond League	1901	7.78 (± 0.35)	7.82	1337 (70.33%)	564 (29.67%)	1833	6.44 (± 0.35)	6.48	1331 (72.61%)	502 (27.39%)
World Championships	586	7.83 $(\pm 0.37)$	7.99	393 (67.07%)	193 (32.93%)	477	6.57 (± 0.30)	6.60	324 (67.92%)	153 (32.08%)
Olympic Games	296	7.83 $(\pm 0.39)$	8.03	207 (69.93%)	89 (30.07%)	297	6.62 (± 0.38)	6.67	191 (64.31%)	106 (35.69%)