An ecological dynamics interpretation of match-wide performance outcomes in elite ISSF air rifle shooting competitions

BALE, Jack Harry <http://orcid.org/0000-0003-3531-3691>, SUPPIAH, Haresh <http://orcid.org/0000-0001-9828-2349>, AHN, Nayun <http://orcid.org/0009-0005-7148-6735>, MCCOSKER, Chris <http://orcid.org/0000-0002-7160-2987>, DAVIDS, Keith <http://orcid.org/0000-0003-1398-6123>, QUIGLEY, Carrie <http://orcid.org/0009-0008-2241-3347> and MIDDLETON, Kane <http://orcid.org/0000-0002-4914-8570>

Original research article

International Journal of Sports Science & Coaching

International Journal of Sports Science & Coaching
1–16

DOI: 10.1177/17479541261447202
journals.sagepub.com/home/spo
Sage

An ecological dynamics interpretation of match-wide performance outcomes in elite ISSF air rifle shooting competitions

Jack Harry Bale[1], Haresh Suppiah[1], Nayun Ahn[1], Chris McCosker[2], Keith Davids[3], Carrie Quigley[4], and Kane Middleton[1]

Abstract

Traditionally, Olympic air rifle shooting research has focused on averaged biomechanical measures or gun-aiming-point trajectory metrics to analyse performance. Most research has been conducted in training environments, with a lack of understanding of competitive performance behaviours in elite shooters. The current study attempts to address both these issues by identifying different shooting behaviours, investigating when they might emerge throughout the duration of a whole match to uncover potentially functional and dysfunctional behaviours. To achieve this aim, a longitudinal K-means cluster analysis was performed on target metrics for individual shooters from the SIUS AG electronic target-scoring systems. Performance data were analysed from various elite competitions, including Grand Prix, Continental Games, World Cups, and the World Championships. Performance data included target metrics such as shot score, shot interval, and X- and Y-coordinates of shot positions. The longitudinal cluster analysis model included 3946 different match performances. Data were split into two clusters of match-wide behaviours. Results indicated that Cluster A (623.15 points) displayed significantly higher match scores than Cluster B (621.64 points). Scoring differences between clusters were mainly in the first 40-shots (excluding the first shot). Athletes in Cluster A took significantly longer to complete all shots throughout a match. Cluster A also exhibits a greater number of shot-by-shot time interval differences in a match, suggesting a possibly greater ability to adapt to changing match constraints, compared with Cluster B. It is concluded that there may be a need for adaptable shooting behaviours to changing match constraints to stabilise shooting performance.

Keywords

Enskilment, International Shooting Sport Federation, performance analysis, target-scoring systems

Introduction

ISSF shooting sports

Olympic air rifle shooting involves shooting 60 pellets, 10 m towards a target within an indoor environment, with points determined by scoring rings. A pellet's centre radial distance to the target centre determines the shot score, with the highest score being 10.9. The indoor environment where air rifle shooting occurs is heavily regulated, with defined target heights, ambient lighting conditions, and range space per shooter. The seemingly-controlled performance environment has driven researchers in air rifle shooting to primarily focus on isolating key determinants of success,[1–4] preferencing biomechanical factors (e.g., centre of pressure),[4–7] and optoelectronic analysis.[8,9]

Reviewer: Ralf Kredel (University of Bern, Switzerland)

[1]Sport, Performance, and Nutrition Research Group, School of Allied Health, Human Services and Sport, La Trobe University, Melbourne, Australia
[2]School of Behavioural and Health Sciences, Australian Catholic University - Brisbane Campus, Brisbane, Australia
[3]School of Sport & Physical Activity, Sheffield Hallam University, Sheffield, UK of Great Britain and Northern Ireland
[4]National Rifle Coach, National Coaching Team, Adelaide, Australia

Corresponding author:
Kane Middleton, Rehabilitation, Nutrition and Sport, La Trobe University, Melbourne, Australia.
Email: middleton@latrobe.edu.au

Only one study has directly compared the effects of training and competition contexts on shooting performance.[1] The authors reported differences in scores and changes in the magnitude of contribution in proposed key indicators of technical determinants of success (i.e., horizontal rifle stability, aiming accuracy, trigger control, and postural balance). All other research has been undertaken in competition simulations where participants shot 60 shots in a training environment.[2,4,7,9] Ihalainen et al.[1] suggested that future research should focus on developing competition preparation strategies and psychological training interventions to manage performance variations between competition and training environments.

To date, no study has evaluated the shooting performance of elite athletes in high-level rifle competitions, such as large Grand Prix, Continental Games, World Cups or World Championships, to understand what and when throughout a match certain performance behaviour could be needed. For example, in other sports it has been shown that long jump behaviours evolve from the first jump, to the next and performance does not remain stable over repeated trials.[10] If a long jumper fouls their first jump, they will change their performance behaviour to jump 'safely' the next attempt (e.g., taking off further from the line), managing risk in their jump performance. Whether behaviour changes during ISSF rifle shooting matches is currently unknown. For example, it is unknown whether key parts of a match, such as the start and end, have different effects on performance behaviour, as observed in other sports.[10,11] Understanding high-level match performance can potentially improve shooters' use of practice time by aiding coaches in creating more representative training environments where coaches can design sessions to enhance performance behaviours observed in competition at specific time points in a match.[12] Pertinent questions include: Are different performance strategies needed at the start of matches compared to the end, or is performance always stable and consistent at the elite level? Performance stabilisation could be achieved through the implementation of strategies such as adjusting break timing or modifying techniques.

A theoretical framework for interpreting shooting match performance

A theoretical area of perceptual-motor learning that seeks to understand how performers' interactions evolve with tasks embedded in a performance environment is ecological dynamics.[12] According to the ecological dynamics perspective, performer actions emerge in various and flexible ways as a person interacts with information from the environment, framed by a performer's specific intentions at a particular moment.[13] This theoretical framework aids practitioners in understanding and assessing the performer-environment relationship by evaluating how human behaviour emerges under interacting constraints.[14] Specifically, ecological dynamics has helped practitioners to understand the nuances of different sport performance contexts and the effects of varying informational constraints in sports like cricket,[15,16] boxing,[17] futsal[18] and long jump.[10]

From an ecological perspective, competition environments are uncertain, evolving, and never stable (see:[19,20]), though the task goal remains the same (i.e., shoot a score as close to 10.9 as possible in each shot). For example, increasing fatigue and the accumulated score could modify performance behaviours over time in shooting performance contexts, or crowds can form near the athlete, changing the environmental constraints on behaviours by increasing noise or disturbing concentration. To navigate these high-pressure environments, it has been argued that performers should learn to wayfind through the 60-shot match, moving from shot 1 to shot 60. A 60-shot match is a form of taskscape, defined as "the performance environment in which people dwell made up of an ensemble of mutually interlocking tasks."[21] The ideas of a taskscape and wayfinding are embedded within the concept of enskilment (i.e., understanding in practice), where learning is inseparable from doing, embedded in the performance context.[21] To be an enskilled wayfinder, one must utilise their perceptions, cognitions, emotions and actions, to navigate through their performance taskscape.[21,22] Enskilment is a suitable social anthropological concept, adopted by the ecological dynamics framework, to interpret how elite ISSF air rifle shooters navigate through their performance environments. This concept can also aid the interpretation of functional, adaptive performance behaviours, which could be used to overcome challenges faced throughout a match, helping interpret performance outcomes.

Investigating shot-by-shot analysis and variability in performance

A significant gap in the ISSF rifle literature is the absence of shot-by-shot analysis, with previous research typically reporting the average values of a performance metric across all 60 shots.[1,2,4,7,9] Analysing performance metrics averaged across a match risks overlooking how the temporal evolution of task and environmental constraints which change performance behaviours of individual athletes within the competitive environment. This analysis could be useful to answer relevant questions like: Is the time it takes for shot five different from shot fifty-five? These data are needed to inform coaches about possible variations and adaptations that may emerge in performance throughout a match, when they occur, and how these changes may be simulated in practice designs. Understanding whether match performances fluctuate is a useful step in determining whether constraints may vary in influence on performance over time and whether there is a possible role for wayfinding to help athletes navigate the competitive environment.

Research in ecological dynamics has uncovered the effects of interacting constraints on athletic performance in long jumping, Taekwondo, kicking and ball disposal in Australian football, and how athletes adopt varying adapting behaviours depending on the constraints acting upon them in the competition environment.[10,23–25] Movement variability and adaptive actions were once considered to be noise in movement systems to be managed and limited, but are viewed in ecological dynamics as functional, supporting overall levels of outcome stability and serving as an injury prevention strategy.[26–34] Performance variability arises from degenerate properties of the organism-environment system.[29] Degeneracy is the capacity of different system elements to perform the same functions or output, and is a functional element of human movement behaviour.[35] Degeneracy is functional, as the body has vast degrees of freedom around limbs and joints and within joint ranges, making it challenging to perform an identical movement pattern over repeated trials.[36] Therefore, it has been shown that skilled performers can exploit inherent system degeneracy in human behaviour to stabilise performance outcomes,[37] indicating that more functional behaviour might be linked to greater variability in some performance metrics, such as time spent per shot.

No research exists on the evolution of behaviours throughout an ISSF air rifle match and how these behaviours could vary. This information could help us understand whether athletes may need to adapt to changing constraints to wayfind throughout an elite competition. There are multiple compensatory shot styles in ISSF air rifle shooting, like precision hold (i.e., low aiming error and mean velocity during the aiming phase), dynamic (i.e., high movement velocity in aiming), and anchored jerk (i.e., similar to precision, with aiming point motion away from the target centre) rifle movements in aiming.[8] However, Tartaruga & Kredel[8] only analysed within-shot behaviours, making it unclear if athletes transition to various shooting styles as they wayfind through a match, demonstrating adaptive changes. Nevertheless, Tartaruga and Kredel[8] acknowledge that athletes may vary their temporal aiming behaviours depending on changing conditions and contextual demands, finding opportunities to modify aiming time or approach behaviours (e.g., changes in shot time intervals) as two of many possibilities. Investigating whether shot time intervals change throughout matches in elite ISSF rifle shooting could provide a rationale for observing how behavioural adaptations may be made in ISSF rifle shooting.

Study aim

The performance of elite shooters in elite-competition environments, and how their functional behaviour evolves across a match, is not well understood. There is currently no research evaluating shot-by-shot performance across a whole ISSF air rifle match, resulting in a lack of understanding of how performance may evolve across the competitive taskscape. Here, we examined the possibility that different stages of a match could impose different constraints on athletes performance behaviours, resulting in them adapting their actions as they navigate the competition taskscape. This study aimed to investigate whether different shooting behaviours across matches could be identified in elite ISSF shooters. Understanding if and how matches evolve will aid in understanding the taskscape that competition rifle shooters must navigate to reach their intended task goals. It was hypothesised that different performance outcome behaviours would be observed in matches, with a range of functional behaviours emerging which stabilise performance outcomes in critical match moments (e.g., especially starting or ending a match).

Research questions

1. How many functional match wide performance outcome behaviours can be identified in elite ISSF air rifle competitions?
2. How does match performance evolve over the course of elite shooting competitions?
3. How stable are the intra-individual match performance behaviours across multiple competitions?

Methods

Ethical approval and data acquisition

The current study obtained ethical exemption from Ethical Integrity and Biosafety (La Trobe University) in accordance with the National Statement on Ethical Conduct in Human Research (2023) (exemption number: EIBX25001). ISSF air rifle shooting results from various high-level competitions - Grand Prix, Continental Games, World Cups, World Championships, World Cup Final, including junior equivalent competitions from 95 different nations between March 2023 and October 2024 from the SIUS AG (Switzerland) cloud platform (https://shootingsportscloud.com/) were gathered using a custom Python script.

Cluster analysis data processing

A longitudinal k-means++ cluster analysis was used to identify subgroups with distinct shooting-behaviour types in the elite population at major competitions, based on the four target-metric trajectories.[38] Unlike standard k-means clustering, which groups independent observations based on static similarity, longitudinal k-means clustering identifies groups of individuals exhibiting similar trajectories over time, thereby accounting for repeated measures and temporal structure in the data.[38] This method partitions the data into distinct behaviour types based on target metrics from SIUS across all imputed shots in a match. By splitting the behaviour types, it's possible to determine whether multiple performance behaviours emerge in a match.

From the SIUS AG cloud platform, four target metrics were extracted for analysis: shot score, time stamps for each shot, and X- and Y-target shot-placement coordinates. The reason for including X- and Y-target shot-placement data, as well as shot score data, is to investigate possible reasons for shot scores by examining X- and Y-bias in coordinate data at different phases of the match. Radial error was not calculated, as shot score is the outcome used to calculate match performance and finishing position, making it the most understandable variable for coaches and practitioners in this context. All shooters had to finish the match within the allocated time without disqualification and shoot exactly 60 shots, or they were not included in the data. A shooter could be represented multiple times in the data if they shot valid matches at various competitions, e.g., if they shot at a World Cup and Europeans, they would have two separate matches in the data.

K-means cluster analysis methods are susceptible to cluster around outliers, especially when data from multiple variables have different data ranges.[39] Before clustering, data on the shot score, shot interval, and X- and Y-coordinates were standardized by centring each feature's mean value and scaling by its standard deviation, placing all data on the same z-scale. The longitudinal k-mean clustering was built using the following configurations: kmeans ++, tested with 2-8 clusters. Each partition was repeated 20 times, Euclidean distance measuring dissimilarities between individual joint-trajectories. Kmeans++ was used to reduce the risk of convergence to a local maximum by selecting initial cluster centres using a weighted random distribution (D^2), ensuring new centres were distant from previously chosen ones.[40] In the current study, we used established criteria to determine the optimal partition and number of clusters (i.e., the Calinski-Harabatz index).[41] Higher indices of this quality criterion indicate better separation between clusters and compactness within clusters. The Calinski-Harabasz index was chosen as the preferred method because it provides a numeric index value to determine the number of clusters, unlike the elbow method, and was explicitly adapted for longitudinal data in the kml3d package.[38,42] The Calinski-Harabasz index method has also been suggested as the more reliable algorithm for testing cluster partitions in non-hierarchical clustering algorithms (i.e., k-means) when assessing the validity of various approaches.[43] All clustering analyses were performed in RStudio (Version: 2024.9.1.394).

Four thousand, ten (4010) 60-shot matches were extracted from the cloud platform. After removing matches with too few or too many shots, 3993 remained. The time stamps were converted into shot intervals (s) between consecutive shots. As a result, shot 1 was removed from the analysis for all target metrics because it lacked a preceding timestamp. The documented match start time is not accurate enough to serve as the preceding timestamp, as matches rarely commence at the exact time they're scheduled to; this inaccuracy would inflate the interval for shot one and be misleading in the performance analysis. Thus, shot one was removed.

Initially these extracted data were included in the longitudinal cluster analysis without additional filtering. However, extreme outliers in scores and shot time intervals caused the model to partition data into 'extreme' and 'normative' values. This focused the identified clusters on the presence of errors rather than functional performance patterns, making it impossible to interpret elite shooting behaviours. Therefore, data filtering was required to examine the research question.

As the research question pertains to functional elite behaviours, the following filtering criteria were applied to the data: any completed match with a score $\leq$ 7.5 on any shot throughout the match was removed from the dataset, leaving 3947 matches. Athletes taking prolonged breaks during the match could also create extreme shot time intervals, skewing the cluster analysis due to the technique's sensitivity. To mitigate this issue, all intervals that exceeded 1.5 standard deviations over the mean of all shots were replaced by their nearest preceding neighbour (14,548 of 232,814 analysed shots; 6.25%). In cases where the preceding shot is not valid, the shot was replaced with the first valid post-nearest neighbour. This imputation approach maintains the temporal structure of the data as a match evolves; for example, if shooters take longer to shoot in one part of a match than in another, this trend has a higher probability of persisting when replacing an invalid shot interval with its nearest valid neighbour. This method is commonly used to minimise information loss while preserving longitudinal performance patterns.[42] It is also common practice when analysing competition data with K-means cluster analysis techniques to manage outliers in the data using imputation techniques.[44] During model testing, one shooter was consistently grouped into a third cluster, characterised by slower times and lower scores than all other shooters. Since the single-member cluster could not perform statistical comparisons, it was deemed an outlier and removed from the final analysis, leaving 3946 matches.

The final input data matrix (3946 matches x 4 features) was then used to perform the longitudinal cluster analysis. By applying this data processing technique, the range of Z-scores was similar across all four variables (Figure 1),

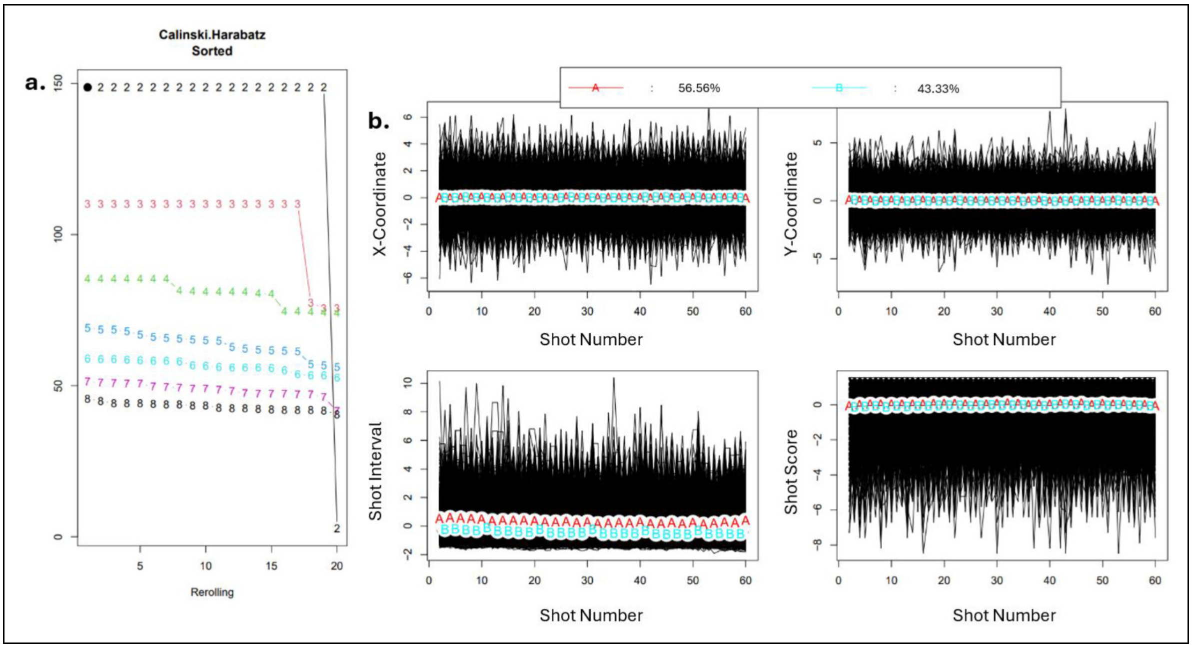

Figure 1. Calinski-Harabasz criterion for cluster analysis quality.
Note. The Calinski-Harabatz index from kml3d is used to assess the quality of partitions. In Figure 1(a), the Y-axis scale indicates a ratio of the between-cluster separation to the within-cluster dispersion. The highest number represents the best cluster selection. The numbers 2-8 represent the range of cluster numbers, and each line with the same number depicts twenty partitions generated with different starting positions by Kmeans++. The black dot marks the selected number of clusters (2 clusters in this case). Figure 1(b) illustrates longitudinal data and visualises the cluster structure of the selected partition using colours (red and cyan).

indicating that no single variable will dominate the clustering solution.

Statistical analysis of cluster difference

Score differences between clusters. An independent-samples *t* test was used to compare differences in the mean score of the 60 shots between the identified clusters. Reported are the *t* test results and the average score for both clusters, including 95% confidence intervals (95% CI).

Linear mixed-effects models comparing clusters and shot-by-shot differences. Linear mixed-effects models were established to evaluate the interaction effects of cluster and shot number on each variable within the statistical analysis. Shot-level data were analysed using linear mixed-effects models, with individual shots nested within matches. Each match comprised a 59-shot sequence and was assigned to a single cluster. Fixed effects included cluster membership and shot order. To account for the non-independence of repeated shots within matches, the models included match-specific random intercepts. The linear mixed-effects models were created in RStudio using the lmerTest package.[45] They were estimated using restricted maximum likelihood (REML) and a bobyqa optimiser. All statistically significant differences emerging among models were assessed using ANOVA. Non-statistically significant models examining the interaction effects of shot number and cluster were simplified by removing the clustering factor from the analysis to assess how matches evolve. This would imply no difference in cluster performance outcomes across the match; however, it is still important to understand whether specific shots in a match differ from others, regardless of cluster allocation. By performing these linear mixed-effects models, it's possible to answer the research questions regarding differences in match-wide behaviours and how matches evolve by examining whether different shots in a match differ from other shots (answering research questions 1 and 2).

Post-hoc comparisons were performed on each cluster outcome at each time point for the significant models. The *post-hoc* tests aid the understanding of which shots were different between clusters and to analyse shot-by-shot differences within clusters. These tests were performed with the emmean package in R studio.[46] Post-hoc power analysis was not conducted. Observed power (calculated from the obtained effect size) is mathematically redundant with p-values and offers no additional inferential value.[47] Instead, we report effect sizes (contrasts) and 95% confidence intervals, which provide more informative estimates of effect magnitude and precision. Additionally, the model's size and complexity made prospective simulation-based power estimation impractical. Contrasts were used on the estimated margin means from the statistically significant models to compare the differences between clusters and shots. Regarding differences in cluster outcome performances, contrasts were created against corresponding shots in each cluster. For shot-by-shot comparisons in a cluster, contrasts were developed to compare one shot against all others (59×58). Contrasts are reported with P-values to indicate whether the effects differ significantly. All *post-hoc* tests had a multiple comparison correction using false discovery rate method.[48] The alpha level for statistical analyses in this study was set to .05.

Exploratory statistics. To compare shot-by-shot differences, the percentage of the maximum range of all significant contrasts around the average was calculated to show how much each cluster varies. To understand how many shots differed to each other, a percentage value was calculated to compare the number of significant shot-by-shot differences in each cluster for shot score and shot time interval. The percentage of significant pairwise shot differences was calculated as the number of contrasts with p-values below .05 among all unique unordered shot pairs (shots 2–60), divided by the total number of possible pairwise comparisons, and multiplied by 100. This calculation was also performed for the first 30 shots (shots 2-30) and the last 30 (shots 31-60). Furthermore, when splitting the match into two, average shot-by-shot contrasts were also calculated, excluding shots where athletes took clear breaks (shots 11, 21, 31, 41, 51), to investigate typical variability in shot time intervals. Shots 11, 21, 31, 41, and 51 were further analysed by comparing their contrast with all other shot time intervals to examine possible differences between shots at the ends of series of 10 shots and those shots taken within the series.

Cluster stability

Intra-individual cluster stability across matches was assessed using a permutation test. Athletes with more than four matches in the cluster were included in order to maintain accuracy by having enough repetitions in the data to account for noise around a mean value as advised in bioinformatics research for cluster analysis methodologies.[49] For each athlete, performance stability was defined as the proportion of matches assigned to their most frequent cluster, and observed stability was calculated as the mean of these proportions across athletes. A null distribution was generated by randomly permuting cluster labels across all matches (1000 permutations) and recomputing mean stability values for each permutation. Statistical significance was evaluated using a one-sided permutation p-value, defined as the proportion of permuted stability values greater than or equal to the observed stability.[50] By performing this stability analysis, it's possible to see how stable athletes' performance behaviours are at the elite level (answering research question 3).

Table 1. Cluster-wise demographic data.

Demographic variable	Cluster A	Cluster B	Total
Number of matches	2232 (56.56%)	1714 (43.44%)	3946
Sex:			
Male	1003 (60.75%)	648 (38.95%)	1651
Female	999 (53.86%)	856 (46.15%)	1855
Unspecified	230 (52.27%)	210 (47.73%)	440
Age:			
Junior (<21 years old)	504 (46.80%)	573 (53.20%)	1077
Senior (≥21 years old)	1728 (60.23%)	1141 (39.77%)	2869
Number of unique athlete nations	89	87	95
Number of unique athletes	868	761	1304

Note. The table counts the number of 60-shot matches performed for each demographic type within each cluster. Percentages are performed row-wise and not within a cluster, so they depict the percentage value of that demographic type in the overall data reported within either Cluster A or B.

Results

Score differences and demographics between clusters

The longitudinal k-mean clustering formed two stable clusters (Figure 1 and Table 1). The mean score of the 60 shots in Cluster A was 623.15, 95% CI [622.86, 623.50] and Cluster B was 621.63, 95% CI [621.26, 622.00], which were statistically significantly different $t_{(3945)} = 6.39$, $p < .001$.

Cluster differences in match performance behaviours

There was a statistically significant interaction effect between shot number and cluster for shot score ($F_{(58, 228694)} = 1.96$, $p < .001$) and shot interval ($F_{(58, 228694)} = 2.97$, $p < .001$) (Figure 2). All shot intervals were statistically significantly different between clusters. The maximum contrast in shot score (Figure 3) was 0.06 points at shot 3 ($p < .001$), with a minimum value of −0.01 at shot 55 ($p = .670$). The maximum shot interval contrast (Figure 3) was 17.75 s, occurring at shot 50 ($p < .001$), with a minimum difference of 13.45 s occurring at shot 32 ($p < .001$).

There was no statistically significant interaction effect between shot number and cluster for the X-coordinate ($F_{(58, 228694)} = 1.10$, $p = .282$) or Y-coordinate models ($F_{(58, 228694)} = 0.69$, $p = .964$).

Shot-by-shot differences in cluster performances

Shot-by-shot differences were calculated separately within cluster for shot score and shot interval in both clusters (Figure 4). Cluster A displayed 7.60% of shot-by-shot score

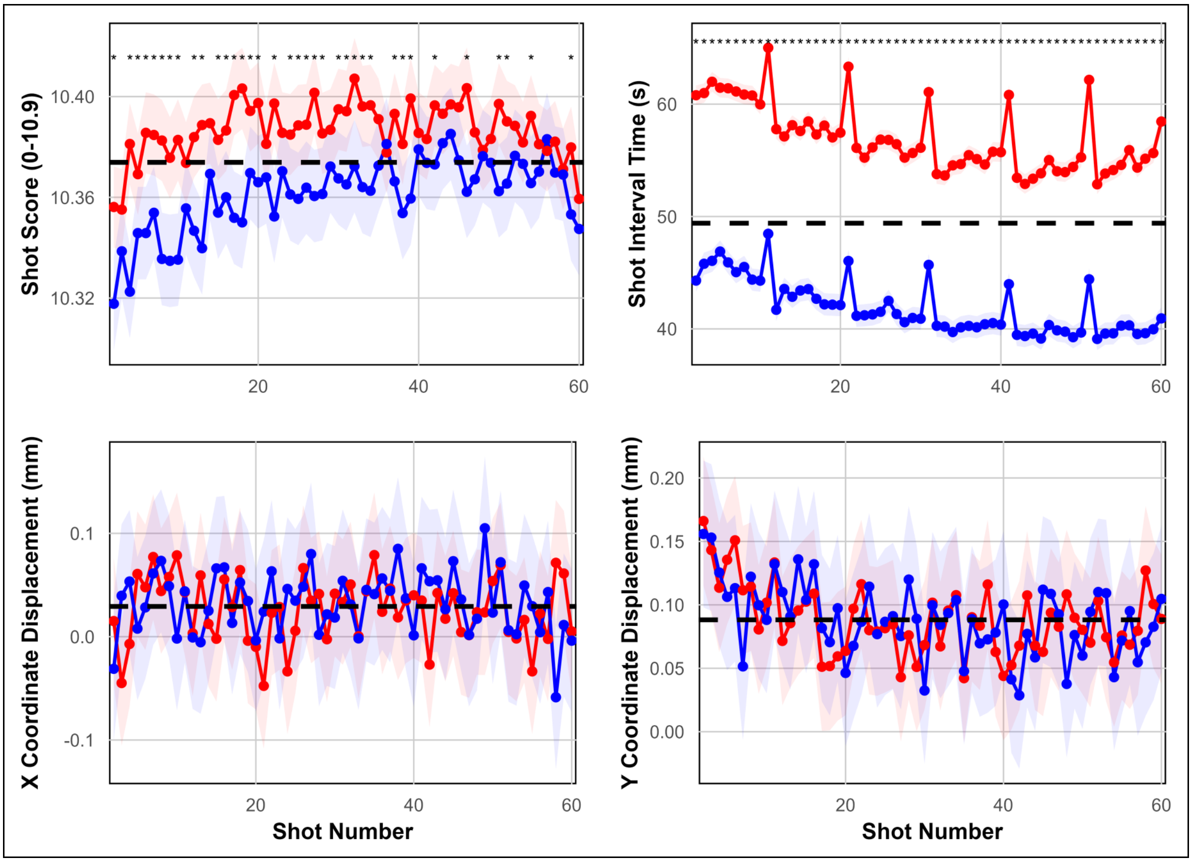

Figure 2. Estimated margin means of the 60-shot match four Sius AG target variables.
Note. Depiction of the estimated margin means for each shot for both clusters (A = Red, B = Blue lines with dots depicting the average for each shot), with a coloured shadow for each shot's 95% confidence interval. The black dashed line represents the overall average value of all shots in both clusters. Due to the X-coordinate and Y-coordinate linear mixed models not being significant, no *post-hoc* tests were performed. * = $p < .05$

differences throughout a match compared to 16.48% in Cluster B. Cluster A also revealed more shot-by-shot shot interval differences over time (76.33%) than Cluster B (63.82%).

The largest absolute shot-by-shot contrast in scores in Cluster A was 0.05 points, compared to Cluster B at 0.07 points. The largest shot-by-shot time interval contrast was 12.15 s compared to 9.36 s, respectively.

When splitting the match in two and removing the large outliers, possibly signifying a break (shots 11, 21, 31, 41, 51), from shot 2 until the 30th shot, Cluster A yielded a maximum contrast of 6.76 s, and Cluster B at 6.29 s. Whereas in the last 30 shots, Cluster A produced a maximum contrast of 5.59 s more than Cluster B at 1.83 s. Cluster A also generated 72.41% significant shot-by-shot interval contrasts until shot 30, with Cluster B having 67.00%. In the last 30 shots, Cluster A produced 56.32% significant shot-by-shot time interval contrasts, while Cluster B yielded only 21.84%.

We analysed the contrast between the time intervals for shots 11, 21, 31, 41, and 51 and those for all other shots. Cluster A had a mean interval of 6.05 s 95% CI [5.70, 6.39] ($p < .001$) and Cluster B had 4.21 s 95% CI [3.82, 4.60] ($p < .001$), showing difference in shot time intervals between series compared to shots within series.

X- and Y-coordinates were retested with just the main effect of shot number, but not cluster, as this would average metrics across the whole match, losing the temporal structure of the data. This modification was undertaken to evaluate the potential for shot-by-shot differences in these variables. The Y-coordinate main effect of shot number was statistically significant ($F_{(58,\ 228752)} = 2.09$, $p < .001$), whereas X-coordinate was not statistically significant ($F_{(58,\ 228752)} = 1.23$, $p = .114$). The Y-coordinate shot-by-shot contrast displayed a 3.74% difference between shots throughout the match, with the largest shot-by-shot contrast being 0.12 mm (Figure 5).

Cluster stability

Among 283 athletes with more than four matches (total = 2509 matches), the observed mean intra-individual stability value in cluster assignments was 0.862, significantly

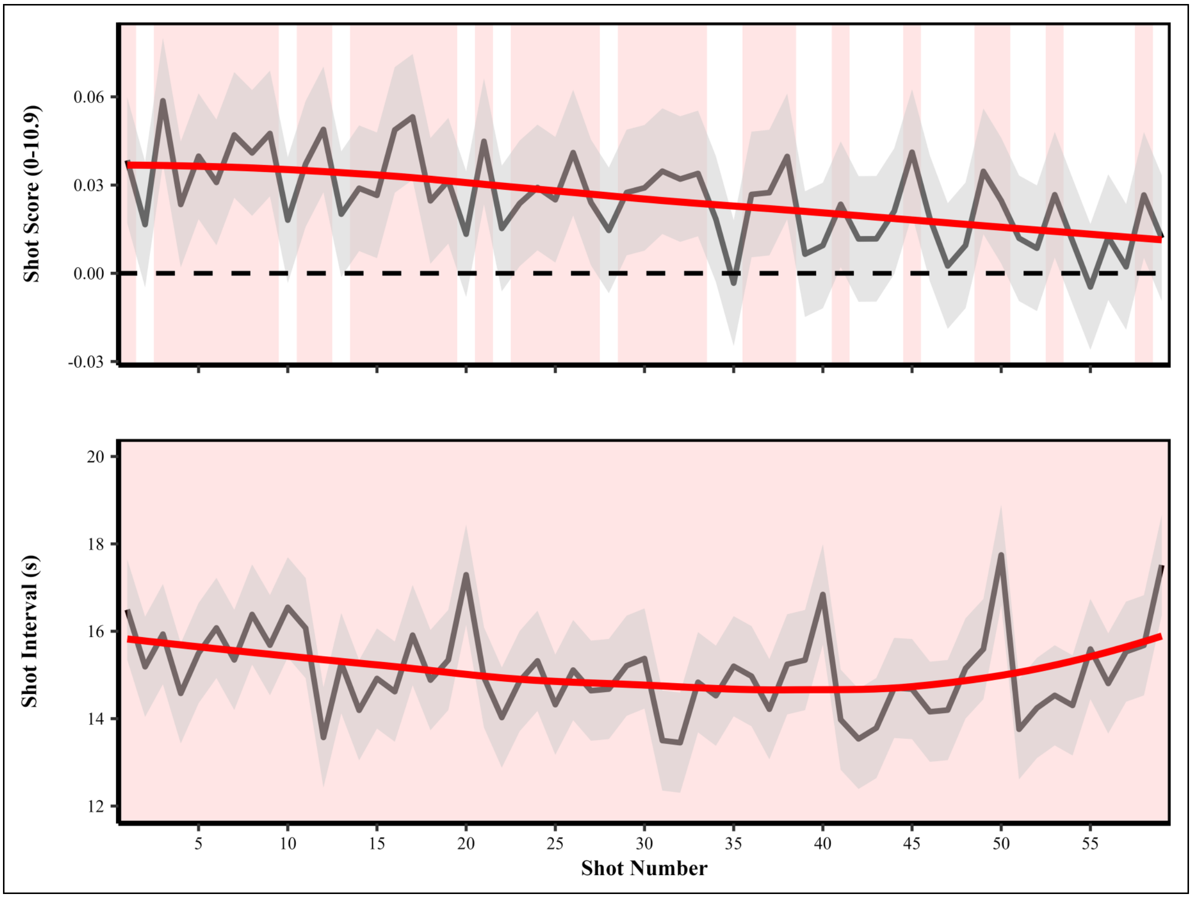

Figure 3. Cluster contrasts across the 60-shot match.
Note. Contrasts are calculated with Cluster A as the reference cluster. The dark grey straight line is the actual contrast value at each time point. The Grey shadow around the straight line is the 95% CI. The red line is the trend of the contrast over the match. The red shadow signified a $p < .05$ in a shot contrast between the two clusters.

exceeding the null expectation of 0.677 ($p < .001$). This finding indicates that athletes consistently belonged to the same cluster across approximately 86% of their matches, rather than randomly switching between clusters.

Discussion

Summary of findings

Using the SIUS target metrics, we investigated how elite ISSF air rifle shooters' match performances evolved over the last fifty-nine shots of a match, examining the possible importance of wayfinding through elite competitions. We also aimed to uncover different shooting behaviours across matches in this elite athlete sample. The longitudinal k-means cluster analysis split match performances into two clusters of behaviours throughout a match duration. Cluster B displayed more shot-by-shot score contrasts than Cluster A (16.48% to 7.60%, respectively), with the first ten shots being the most different to other groups of shots in the match, with larger contrasts than Cluster A (maximum shot-by-shot contrast value: 0.07 points to 0.05 points, respectively). This performance pattern led to lower overall match scores for Cluster B (621.64 points) than for Cluster A (623.15 points). The many shot-by-shot differences observed in scoring and shot interval (Figure 4) within each participant in both clusters provided evidence that phases of a match exerted varying constraints on shooters, with behaviours being adapted, with very few shots being performed in an identical manner.

Cluster differences in match performance behaviours

Results show that both clusters shot lower scores in the first part of the match, Cluster B more so than A. There is no research on why the start of shooting matches may display lower shot scores in Olympic rifle shooting. For example, there could be individual differences in cognition, action and perception to consider between initial sighting shots (i.e., centring the rifle aim) and phases of the match. Any potential differences could be due to athletes needing to search at the start of matches for knowledge of their

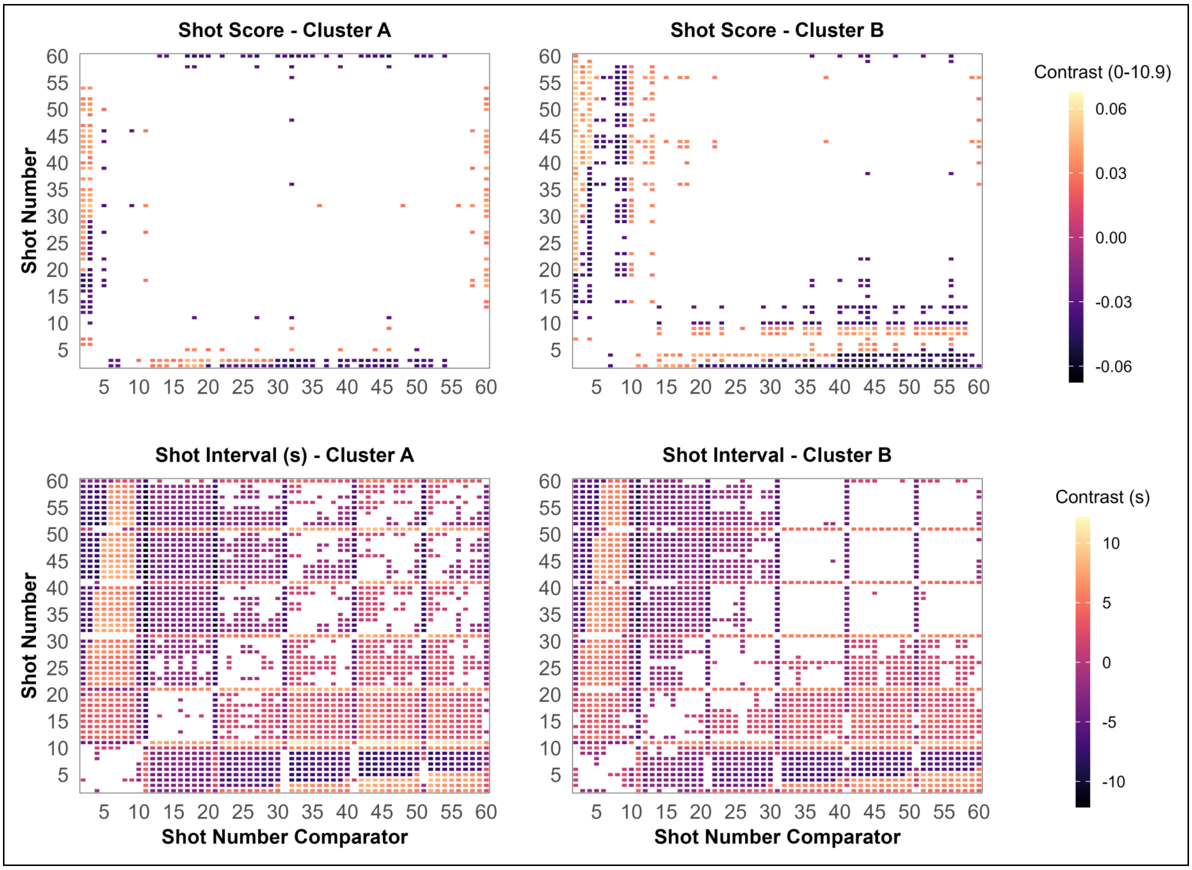

Figure 4. Shot-by-shot contrast heat map for shot score and shot intervals between clusters.
Note. The heat map's coloured-squares denote significant contrast values, displaying the contrast differences between different shots. The shot-by-shot contrast was not statistically significantly different if a square is white.

environment and specifying information (i.e., information most useful for task success)[51] emerging from varying conditions.[21] This search for information by the athletes has been observed in other sports like table tennis, where players seek to explore and validate their knowledge of their opponents' behaviours at the start of matches by modifying their own behaviours at the beginning.[11] In the table tennis performance context, each new opponent presents new task constraints for the player. In rifle shooting at a different scale, each shot could also exhibit new task constraints for adaptation, especially from initial sighting to the first few shots of the match. For example, cognition has been observed to change between practice and match conditions in the sport of taekwondo, affecting fighters' behaviours revealed in performance variables such as attack distance and attack frequency.[23] It is possible that this change in cognition could also occur in the sport of ISSF rifle shooting, warranting further investigation, especially regarding the changes in coordination at match onset.

Exploratory behaviour could emerge in ISSF rifle shooting as athletes start slower, possibly giving themselves time to understand their interactions with their environment and learn to adapt to the uncertainty of emerging informational constraints (e.g., potential changes in cognition[52] or muscle tension).[53] To exemplify, Cluster A's first ten shots were slower than many other shots in participants of both cluster allocations (Figure 4), except for the tenth shot in every series, where athletes take a break (series are made up of ten shots). This difference could be due to exploratory behaviours emerging in these first shots of a match.

Learning to perform on a particular day requires an ability to self-regulate performance behaviours to adapt to changing informational constraints, with shooters using perception, action, and cognition to navigate the competitive environment to achieve their intended task goals. They can achieve this aim by being highly attentive to information within their performance context.[21,22] Indeed, this is a key ability of elite athletes across sports, supporting them to functionally adapt their actions to evolving task and environmental constraints.[54,55] This is a key characteristic of enskilled wayfinders, who can regulate their behaviours as they navigate through their performance context.[20–22] The data reported here could imply that shooting performance could be improved by enhancing the capacity for self-regulation and adaptable behaviours during competitive performance as constraints change, especially at the start

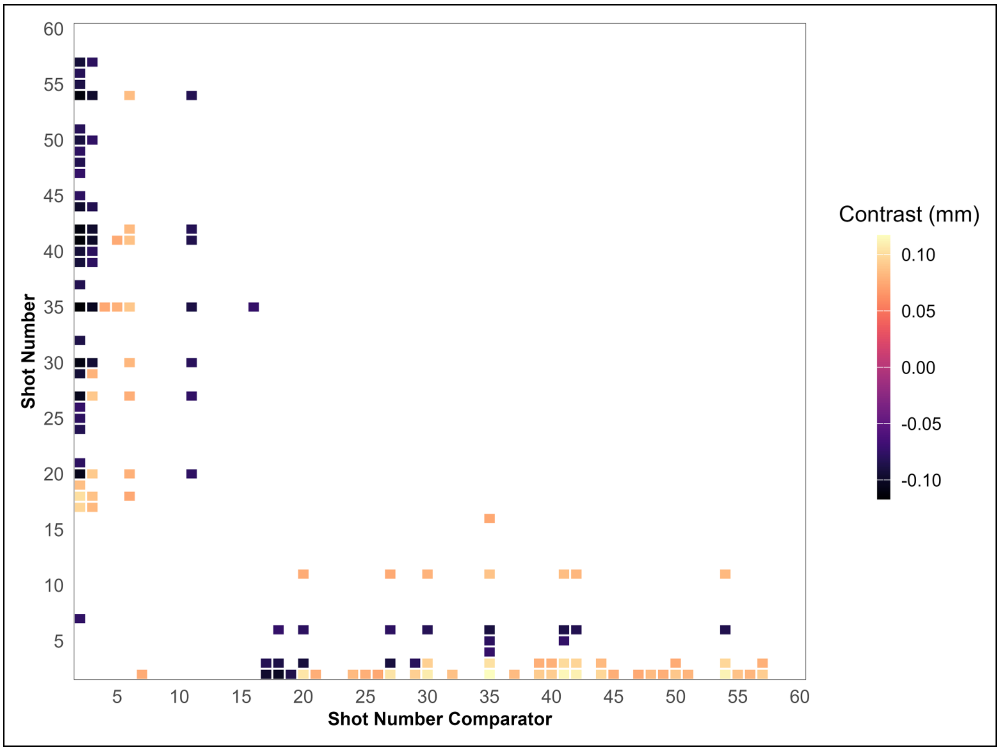

Figure 5. Shot-by-shot contrast heat map for Y-coordinates.
Note. The heat map's coloured-squares denote significant contrast values, displaying the contrast differences between different shots. The shot-by-shot contrast is not statistically significantly different if a square is white.

of matches. For example, at the beginning of matches, the task constraints change significantly as the score for each shot accumulates, and these changes can interact with other constraint types, such as individual or social constraints (e.g., intentionality, arousal, or pressure to perform).

To exemplify, there could be an increased benefit for behavioural regulation and adaptive behaviours at the start of matches, with significant Y-coordinate bias shown to be a result of participants placing the initial few shots a maximum of 0.12 mm higher than the subsequent ones (Figure 5). Common potential causes of shots landing high on the target may include anxiety and competitive stressors, which have been shown to increase muscle activation and self-reported stress indicators in ISSF air pistol shooting.[56] Muscle activation increases have also been noted in golf, where players excessively try to physically constrain their actions during high-pressure situations.[57] Given the evident decline in performance at the outset, researchers and coaches could develop innovative strategies, behavioural adaptations, and representative environments to address interacting task and personal constraints during the early stages of matches. This strategy could involve use of breathing techniques,[58] self-talk,[59] mental imagery,[60,61] biasing the aim slightly lower initially by lowering the rifle sights on the first few shots, dry-firing after the start command, or taking additional time to set the position and aim. Nonetheless, the data suggest that strategies for managing the start of the match are needed, which is a challenge for coaches and sports scientists.

It is possible that shooters also failed to prepare sufficiently before the first match shot; for example, it is possible that they did not sight the gun correctly, which could bias the Y-coordinate data at the start of matches. At the elite level, this possibility is unlikely to occur frequently and may not always lead to high shots. Changes in match constraints at the onset of the competition are more likely to be the cause of the Y-coordinate shot-by-shot difference.

Shot-by-shot differences in cluster performance

To facilitate discussion of skilled performance and to understand the functionality of behavioural change across the two clusters, shot-by-shot intervals were analysed by cluster. Cluster A had more significant contrasts in shot-by-shot intervals (Cluster A: 76.33%, Cluster B: 63.82% shot-by-shot differences). These distinct shots exhibited a wider range of intervals than those match performances in Cluster B (Cluster A: 12.15 s, Cluster B: 9.36 s maximum contrasts). Variability was greater throughout a match in participants of Cluster A, possibly indicating a broader spectrum of skilful behavioural adaptations contributing to enhanced shooting performances. Increases in exploiting behavioural degeneracy, through adaptive variability, have been observed in other sports, such as basketball, for stabilising shot-outcome performance.[62] Degeneracy is the ability of elements of a system (e.g., segments and joints in the body) that are structurally different to perform the same function or yield the same outcome.[35] It has previously been proposed that flexibility within human behaviour can aid in adapting to changing constraints and environmental uncertainty, stabilising performance outcomes.[34] As Cluster A revealed more variability in shot intervals and magnitude between shots, but resulted in greater performance stability, it could be possible that athletes in this grouping were more functionally adaptable and able to employ a wider range of behaviours depending on constraints in the performance context, seeking to keep their performance outcome more stable.

Participants in Cluster B showed more behavioural stability in the second half of the match, with only 21.84% different shot-by-shot intervals, where their performance was at its best, compared to 67.00% in the first twenty-nine shots. Excluding shots with possible breaks, the magnitude of behavioural change within the first half of the match was greater (maximum contrast: 6.29 s) compared with the last half (maximum contrast: 1.83 s). This could demonstrate that those athletes in Cluster B had a smaller range of functionally adaptable behaviours that can be applied to adapt to changing match conditions. This possible lack of functional adaptability could lead to a struggle to adapt to the start of matches where constraints may push their behaviour coordination outside the bounds they can manage, leading to greater drops in performance at the start of the match compared to Cluster A, where athletes first twenty-nine and last thirty shots showed more similar and greater magnitudes of variability (maximum contrasts: 6.76 s to 5.59 s, respectively). This possible lack of functional adaptability has been previously observed in novice rock climbers, who display more rigid behaviour than their more skilled counterparts and take longer to climb ice walls.[63,64] This same phenomenon has been observed in darts, where an entropy analysis of movement variability in joint angles, velocities, and accelerations during a dart-throwing accuracy task revealed improved performance.[65] Therefore, a level of variability in shooting sports could be functional[66] and possibly observed in Cluster A in elite competitions.

It is possible that athletes in Cluster B may have run out of time, reducing the time they have per shot and constraining their adaptability. If this were the case, time may not have been used functionally beforehand, and more enskilling is required through enhanced opportunities to functionally adapt their actions to changing temporal constraints on achieving the task goal, like those in Cluster A. In this way, better performance in ISSF air rifle competitions may be linked to being an enskilled, wayfinding athlete. To determine the validity of this argument, the within-shot behaviours and their changes across a match need to be analysed. This current study provides initial evidence that there is a need to look further at the possible role of adaptive behaviours in ISSF rifle shooting.

Post-hoc break behaviour observations

The timing data also shows a behavioural strategy in elite shooting performances regarding the timing of small micro-breaks. After every ten shots, both clusters display clear peaks in shot time intervals, indicating a short break period (Figure 2). These peaks are evident in the data, even with the removal of extreme values. Cluster A had an average of 6.05 s, and Cluster B had 4.21 s longer tenth shot in a series shot time interval compared to all other shot intervals, which could be an artificially smaller value than what the average difference was because of data imputation techniques for the cluster analysis. There are a few possible explanations for this finding: (1) the SIUS system could exhibit a time delay before storing the first shot of each new series, though shots are stored individually in the system; (2) This behaviour may have a form of anchoring bias,[67] where athletes will finish a string of ten shots because the scores are grouped in ten-shot strings on the leaderboard, so those shots could be perceived as belonging together; (3) It could also be a taught behaviour, where coaches advise taking a break every 10 shots. Indeed, some coaching manuals discuss using pre-defined, pre-agreed breaks with their athletes.[68,69] The functionality of this behaviour requires further investigation to determine whether it aids performance and whether there may be other break strategies that could further improve performance. An enskilled, wayfinding athlete would be hypothesised to rest when necessary, attuned to information indicating the need for a break, regardless of whether that occurs at a random shot number throughout a series. The potential issue with only breaking every ten shots is that if shot eleven is poor, athletes may feel compelled to continue until shot twenty. The predetermined strategy for breaks could overrun any need for adaptation, eliminating the need for prospective information to control behaviour and wayfind to task goals.[70] Therefore, pre-determined break strategies in ISSF rifle competitions may not be based on breaking when needed and self-regulation in these elite athletes, rather than on pre-planned strategies, require further investigation.

Cluster stability

When investigating the stability of cluster assignments for those athletes with multiple matches in the data set (i.e., more than four), the athletes' intra-individual stability value was 86%. The data reveal that athletes typically exhibit the same match-wide behaviours in performance outcomes, and clustering remains stable. For example, athletes who are slower throughout the match typically remain slow in other matches. This could mean their ability to skilfully wayfind is stable across multiple ISSF air rifle match environments.

Trying to uncover the reasons for the proportion of intra-individual behavioural instability could be valuable in identifying which task and environmental constraints could perturb athletes' performance behaviour, leading to a phase change into a new match-wide behavioural pattern. These could include time constraints, scoring-accumulation task constraints, or fatigue; however, the effects of these constraints on match-wide behaviours need further investigation.

Future research direction and limitations

The direction of future research into ISSF rifle shooting should focus on uncovering specific shooting behaviours of elite athletes under match conditions and the behavioural adaptations they employ to maintain stable performance outcomes in competition. This can be achieved by avoiding averaging performance metrics over a whole match and splitting the 60-shot match into sections, on which impinging interacting constraints may elicit different behaviours. Research should seek to understand how constraints change throughout match conditions, framed by intentionality. For instance, understanding how intentionality evolves and how elite athletes self-regulate their intentions, emotions, and cognitions could assist coaches in designing representative environments aimed at challenging this regulation in ways needed during competition.[10,71,72] Air rifle competition environments remain stable in front of the firing line due to stringent regulations (e.g., lighting, airflow, distance). However, the changing task constraints from sighting to the match start could alter intentionality and, in turn, influence behaviour. Future research should seek to understand how a shooter's intentions evolve as matches progress and what information athletes are attuned to, which could be explored through eye-tracking technologies.[73]

A caveat and limitation of the current data is that it is not clear why behaviour adapts throughout a match, or whether this adaptation is always functional. It is likely contextual in nature. For example, changes in shot-by-shot time intervals could be implemented for enhancing performance functionality, or they could be forced by time constraints that require athletes to rush to finish the match. In the latter case, behavioural adaptations, whether greater time-interval stability or not, could be dysfunctional for performance outcomes. Future research should seek to investigate this distinction by examining match-wide behaviours using multiple methodologies and statistical techniques, as cluster analysis can require substantial data processing to create stable clusters, as reported here.[44]

This study evaluates how shooters progress through the 60-shot taskscape at the shot-by-shot level. A taskscape can be divided into numerous nested units of tasks.[21,74] Future research needs to examine what athletes are doing within each shot (e.g., aiming for longer, spending more time to develop their position) to determine why there are larger shot intervals at the beginning compared with the end of a 60-shot match. ISSF rifle shooting practitioners may consider implementing analytical devices to better understand shooting performance, like the extensive array of sensors used in Formula One cars[75] or the player-tracking units used in Australian rules football to evaluate performance.[76] In ISSF rifle shooting, inertial measurement units could be embedded in rifles, providing insights into athletes' behaviours during shots. If it were possible to measure rifle end-point control or aiming point trajectory in competitive environments, it would enable a better understanding of various behavioural strategies during the shot, including possible shot types like precision hold, dynamic, and anchored jerk rifle movements in aiming, as observed in a cluster analysis of different within-shot behaviours.[8] It would also be possible to understand the specific changes athletes employ in their shot behaviours, which take varying amounts of time throughout a match, and how these may evolve. This is a limitation of the current study, as it is not currently possible to evaluate kinematic data, rifle end-point control, aiming point trajectory, or other metrics of behaviour, such as gaze behaviour, in competition due to the structure of current ISSF rules. For instance, athletes might begin with a more anchored jerk behaviour in their rifle aiming point trajectory and transition into a more precise hold style of shooting as they progress through a match. This more in-depth analysis of behaviour is currently not permitted in competition.

From the data, it is not clear what constraints may be changing and modifying shot time intervals or match scores. Constraints impose limits or allow the emergence of coordinated actions.[14] As constraints interact, subtle changes in constraints can modify behaviour into new patterns.[77] A limitation of using target outcome metrics is that it is not clear which behaviours are subtly changing over time. This current paper provides evidence that behaviours change. Understanding why they may change is an important next step for future research.

This study employed longitudinal cluster analysis and identified two clusters with distinct shooting behaviour. The longitudinal cluster analysis identified two 60-shot, match-wide behavioural trajectories that transcend sex, age, nationality, and finishing position. Based on this analysis, future research should explore shot-by-shot changes within all these categorical variables. For instance, do finalists in ISSF air rifle competitions exhibit different behaviours and performances over time than athletes in various quartiles on the leaderboard?

A minor limitation of this study is the exclusion of shot one from the analysis. This was necessary because there was no reliable reference time point before this shot to create a shot interval. The SIUS target data only provides a global timestamp, not one anchored to the match clock, so shot 1 has no preceding timestamp. The inclusion of a match clock timestamp would aid understanding of match behaviour from shot one. If a time variable anchored to the match lock existed, it would be possible to include time remaining as a covariate, allowing greater exploration of match behaviours and understanding whether pacing changes represents a functional adaptive behaviour or a forced adaptation that is required to complete the match within the remaining task time constraint.

Although it might typically have been preferable not to use reduction or imputation methods on the raw data, the use of a longitudinal k-means cluster analysis required such an approach. Without filtering outlying data, the cluster analysis was driven by extreme outliers and may not have revealed elite functional behaviours. Therefore, this may be considered a limitation of the data for shot score and shot time intervals, and the interpretation of break behaviours in full is not possible. It is also not possible to infer from the treated data the effects of match time constraints on performance, i.e., distinguishing those participants who run out of time to finish the match. Future work should investigate break behaviours in ISSF air rifle matches in detail. Furthermore, some thresholds were arbitrarily chosen, such as the 7.5 score threshold for identifying a score outlier. This was conducted to ensure the cluster analysis did not return a cluster centroid solution that would depict those who made a mistake and those who did not. The same applies to the 1.5 times standard deviation filter for the shot time intervals. Applying these filters yielded a stable, repeatable clustering solution with similar data ranges between the four factors.

Within the data set, multiple measures are reported for a few athletes (i.e., 283 had > 4 entries). This could provide an insightful large case study of shooting performers over several trials, although included in a large sample, it could potentially bias the data set analysis towards the specific patterns of behaviour displayed by these athletes. However, these behaviours are still observed in elite air rifle shooting matches, occurring on different days under potentially different constraints that affect performance.

In the data, there were no changes in the X-coordinate over time or between clusters. This could be due to athletes being right and left-handed in the data, cancelling out effect sizes in a given direction. Unfortunately, it is not possible to know the handedness of athletes from the SIUS target data and not every profile includes this information on the ISSF athlete search pages (https://www.issf-sports.org/athletes). Therefore, this is a limitation of the data used in this study.

Conclusion

Invoking the social anthropological concept of enskilment and the related interpretation of wayfinding in the study of shooting, indicators of performance behaviours, such as shot time interval and score, were observed to vary throughout a match. Specific periods of a competitive match differ in context from one another, particularly at the start. This investigation found evidence of enskilled wayfinding in these competitions, with a group of match performances (identified as Cluster A in this study) in which athletes scored better and demonstrated more shot-by-shot time interval differences, possibly indicative of adaptive behaviours throughout a match. Therefore, coaches should seek to consider the value of this evidence of performance variability, implicating the idea that matches have different phases and task constraints which continually act on shooting athletes. These findings align well with data reported from other sports indicating the significance of skill adaptation being developed in athletes. The next step in this line of enquiry is to understand which specific task constraints change over the course of a match and how athletes modify their behaviours to satisfy these influences.

Acknowledgements

The authors would like to acknowledge SIUS AG's support and openness in allowing us access to the data on their shooting cloud service used in this study.

ORCID iDs

Jack Harry Bale https://orcid.org/0000-0003-3531-3691
Haresh Suppiah https://orcid.org/0000-0001-9828-2349
Nayun Ahn https://orcid.org/0009-0005-7148-6735
Chris McCosker https://orcid.org/0000-0002-7160-2987
Keith Davids https://orcid.org/0000-0003-1398-6123
Carrie Quigley https://orcid.org/0009-0008-2241-3347
Kane Middleton https://orcid.org/0000-0002-4914-8570

Ethical considerations

The current study obtained ethical exemption from Ethical Integrity and Biosafety (La Trobe University) in accordance with the National Statement on Ethical Conduct in Human Research (2023) (exemption number: EIBX25001).

Consent to participate

Not applicable.

Consent for publication

Not applicable.

Funding

The authors received no financial support for the research, authorship, and/or publication of this article.

Declaration of conflicting interests

The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

References

1. Ihalainen S, Mononen K, Linnamo V, et al. Which technical factors explain competition performance in air rifle shooting? *Int J Sports Sci Coach* 2018; 13: 78–85.

2. Ihalainen S, Kuitunen S, Mononen K, et al. Determinants of elite-level air rifle shooting performance. *Scand J Med Sci Sports* 2016; 26: 266–274.
3. Ihalainen S, Linnamo V, Mononen K, et al. Relation of elite rifle shooters' technique-test measures to competition performance. *Int J Sports Physiol Perform* 2016; 11: 671–677.
4. Lang D and Zhou A. Determinants of shooting performance in elite air rifle shooters. *Sports Biomech* 2024; 23: 2708–2718.
5. Ball KA, Best RJ and Wrigley T V. Inter-and intra-individual analysis in elite sport: pistol shooting. *J Appl Biomech* 2003; 19: 28–38.
6. Sundaram V, Sundar V and Middleton K. Technical determinants of air rifle and pistol shooting performance: a systematic review and meta-analysis. *Int J Sports Sci Coach* 2024; 19: 1844–1862.
7. Lang D and Zhou A. Relationships between postural balance, aiming technique and performance in elite rifle shooters. *Eur J Sport Sci* 2022; 22: 1493–1498.
8. Tartaruga D and Kredel R. Effects of inter- and intraindividual compensation-sensitive shot styles on performance in Olympic air rifle shooting. *Curr Iss Sport Sci* 2024; 9: 1–17.
9. Bale JH and Wilkinson M. Validity and reliability of an optoelectric training system in elite and national level ISSF air rifle shooters. *Sports Eng* 2023; 26: 27.
10. McCosker C, Renshaw I, Greenwood D, et al. How performance analysis of elite long jumping can inform representative training design through identification of key constraints on competitive behaviours. *Eur J Sport Sci* 2019; 19: 913–921.
11. Sève C, Poizat G, Saury J, et al. A grounded theory of elite male table tennis Players' activity during matches. *The Sport Psychol* 2006; 20: 58–73.
12. Araújo D, Davids K and Passos P. Ecological validity, representative design, and correspondence between experimental task constraints and behavioral setting: comment on Rogers, Kadar, and Costall (2005). *Ecol Psychol* 2007; 19: 69–78.
13. Araújo D, Davids K and Hristovski R. The ecological dynamics of decision making in sport. *Psychol Sport Exerc* 2006; 7: 653–676.
14. Davids K, Button C and Bennett S. *Dynamics of skill acquisition: a constraints-led approach*. Book, Champaign, IL: Human Kinetics, 2008.
15. Pinder RA, Davids K and Renshaw I. Metastability and emergent performance of dynamic interceptive actions. *J Sci Med Sport* 2012; 15: 437–443.
16. Pinder RA, Davids K, Renshaw I, et al. Manipulating informational constraints shapes movement reorganization in interceptive actions. *Atten Percept Psychophys* 2011; 73: 1242–1254.
17. Hristovski R, Davids K, Araújo D, et al. How boxers decide to punch a target: emergent behaviour in nonlinear dynamical movement systems. *J Sports Sci Med* 2006; 5: 60–73.
18. Travassos B, Duarte R, Vilar L, et al. Practice task design in team sports: representativeness enhanced by increasing opportunities for action. *J Sports Sci* 2012; 30: 1447–1454.
19. Morris CE, Davids K and Woods CT. On the wisdom of not-knowing: reflections of an Olympic Canoe Slalom coach. *Sport Educ Soc* 2024; 29: 385–396.
20. Woods CT and Davids K. "You Look at an ocean; I see the rips, hear the waves, and feel the currents": dwelling and the growth of enskiled inhabitant knowledge. *Ecol Psychol* 2021; 33: 279–296.
21. Woods CT, Rudd J, Gray R, et al. Enskilment: an ecological-anthropological worldview of skill, learning and education in sport. *Sports Med Open* 2021; 7: 1–9.
22. Woods CT, Rudd J, Robertson S, et al. Wayfinding: how ecological perspectives of navigating dynamic environments can enrich our understanding of the learner and the learning process in sport. *Sports Med Open* 2020; 6: 1–11.
23. Maloney MA, Renshaw I, Headrick J, et al. Taekwondo fighting in training does not simulate the affective and cognitive demands of competition: Implications for behavior and transfer. *Front Psychol* 2018; 9: 1–13.
24. Browne PR, Sweeting AJ, Davids K, et al. Prevalence of interactions and influence of performance constraints on kick outcomes across Australian football tiers: implications for representative practice designs. *Hum Mov Sci* 2019; 66: 621–630.
25. Teune B, Woods C, Sweeting A, et al. The influence of individual, task and environmental constraint interaction on skilled behaviour in Australian football training. *J Sports Sci* 2022; 40: 1991–1999.
26. Andrews MH, Gorman AD and Crowther RH. Functional movement variability to maintain delivery speed in cricket fast bowling. *Eur J Sport Sci* 2024; 24: 415–421.
27. Hamill J, Palmer C and Van Emmerik REA. Coordinative variability and overuse injury. *Sports Med, Arthroscopy, Rehabil, Ther and Technol* 2012; 4: 1–9.
28. Beck D, Hossner EJ and Zahno S. Mechanisms for handling uncertainty in sensorimotor control in sports: a scoping review. *Int Rev Sport Exerc Psychol* 2025; 18. DOI: 10.1080/1750984X.2023.2280899
29. Seifert L, Komar J, Araújo D, et al. Neurobiological degeneracy: a key property for functional adaptations of perception and action to constraints. *Neurosci and Biobehav Rev* 2016; 69: 159–165.
30. van Emmerik RE, van Wegen EE, Emmerik V, et al. On the Functional Aspects of Variability in Postural Control, www.acsm-essr.org (2002).
31. Davids K, Glazier P, Ará Ujo D, et al. Movement systems as dynamical systems the functional role of variability and its implications for sports medicine. *Sports Med* 2003; 33: 245–260.
32. Bartlett R. Movement variability and its implications for sports scientists and practitioners: an overview. *Int J Sports Sci Coaching* 2008; 3: 113–124.
33. Preatoni E, Hamill J, Harrison AJ, et al. Movement variability and skills monitoring in sports. *Sports Biomech* 2013; 12: 69–92.
34. Bartlett R, Wheat J and Robins M. Is movement variability important for sports biomechanists? *Sports Biomech* 2007; 6: 224–243.

35. Edelman GM and Gally JA. Degeneracy and complexity in biological systems. *Proc Natl Acad Sci* 2001; 98: 13763–13768.
36. Bernstein N. *The co-ordination and regulation of movements*. Oxford: Book, Pergamon Press, 1967.
37. Kelso JAS. Multistability and metastability: understanding dynamic coordination in the brain. *Philos Trans R Soc, B* 2012; 367: 906–918.
38. Genolini C, Falissard B, Kiener P, et al. kml3d: K-Means for Joint Longitudinal Data., https://CRAN.R-project.org/package=kml3d (2024, accessed 6 January 2025).
39. Mohamad I B and Usman D. Standardization and its effects on K-means clustering algorithm. . *Res J Appl Sci, Eng Technol* 2013; 6: 3299–3303.
40. Arthur D and Vassilvitskii S. k-means++: The advantages of careful seeding. In: *Proceedings of the eighteenth annual ACM-SIAM symposium on Discrete algorithms*, New Orleans, Louisiana, 2007, pp.1027–1035. Philadelphia, PA: Society for Industrial and Applied Mathematics.
41. Caliński T and Harabasz J. A dendrite method for cluster analysis. *Commun in Stat* 1972; 3: 1–27.
42. Genolini C, Alacoque X, Sentenac M, et al. kml and kml3d: R Packages to Cluster Longitudinal Data. *J Stat Softw* 2015; 65: 1–34.
43. Shim Y, Chung J and Choi I-C. A comparison study of cluster validity indices using a nonhierarchical clustering algorithm. In: *International conference on computational intelligence for modelling, control and automation and international conference on intelligent agents, web technologies and internet commerce (CIMCAIAWTIC'06)*, Vienna, Austria, 2005, pp.199–204. NW Washington, DC: IEEE Computer Society.
44. An N. Sports competition data analysis and strategy optimization using K-means clustering algorithm. *J Comput Methods Sci Eng* 2025; 25: 888–902.
45. Kuznetsova A, Brockhoff PB and Christensen RHB. Lmertest package: tests in linear mixed effects models. *J Stat Softw* 2017; 82: 1–26.
46. Lenth RV, Banfai B, Bolker B, et al. Estimated marginal means, aka least-squares means. *Am Stat* 2024; 34: 216–221.
47. Hoenig JM and Heisey DM. The abuse of power. *Am Stat* 2001; 55: 19–24.
48. Benjamini Y and Hochberg Y. Controlling the false discovery rate: a practical and powerful approach to multiple testing. *J R Stat Soc Series B Stat Methodol* 1995; 57: 289–300.
49. Sloutsky R, Jimenez N, Swamidass SJ, et al. Accounting for noise when clustering biological data. *Brief Bioinform* 2013; 14: 423–436.
50. Morais JE, Silva AJ, Marinho DA, et al. Cluster stability as a new method to assess changes in performance and its determinant factors over a season in young swimmers. *Int J Sports Physiol Perform* 2015; 10: 261–268.
51. Gibson JJ. *The ecological approach to visual perception*. Houghton, Mifflin and Company, 1979.
52. Zhang J, Shi Y, Wang C, et al. Preshooting electroencephalographic activity of professional shooters in a competitive state. *Comput Intell Neurosci* 2021; Article ID 6639865. DOI: 10.1155/2021/6639865
53. Renshaw I, Davids K, O'Sullivan M, et al. An ecological dynamics approach to motor learning in practice: reframing the learning and performing relationship in high performance sport. *Asian J Sport Exerc Psychol* 2022; 2: 18–26.
54. Phillips E, Davids K, Renshaw I, et al. Expert performance in sport and the dynamics of talent development. *Sport Med* 2010; 40: 271–283.
55. Bennett KJM and Fransen J. Distinguishing skill from technique in football. *Sci Med Footb* 2024; 8: 397–400.
56. Loh SK, Lim JZ, Pan JW, et al. Air pistol shooting: upper limb muscle activation between training and simulated competition. *Sports Biomech* 2024; 23: 1726–1737.
57. Cooke A, Kavussanu M, Mcintyre D, et al. Effects of competitive pressure on expert performance: underlying psychological, physiological, and kinematic mechanisms. *Psychophysiology* 2011; 48: 1146–1156.
58. Migliaccio GM, Russo L, Maric M, et al. Sports performance and breathing rate: what is the connection? a narrative review on breathing strategies. *Sports* 2023; 11: 1–10.
59. Hatzigeorgiadis A, Galanis E, Zourbanos N, et al. Self-talk and competitive sport performance. *J Appl Sport Psychol* 2014; 26: 82–95.
60. Liu Y, Zhao S, Zhang X, et al. The effects of imagery practice on athletes' performance: a multilevel meta-analysis with systematic review. *Behav Sci* 2025; 15: 1–23.
61. Boschker MSJ, Bakker FC and Michaels CF. Effect of mental imagery on realizing affordances. *Quarterly Journal of Experimental Psychology Section A: Human Experimental Psychology* 2002; 55: 775–792.
62. Rein R, Davids K and Button C. Adaptive and phase transition behavior in performance of discrete multi-articular actions by degenerate neurobiological systems. *Exp Brain Res* 2010; 201: 307–322.
63. Seifert L, Wattebled L, L'hermette M, et al. Inter-limb coordination variability in ice climbers of different skill level. *Balt J Sport Health Sci* 2011; 1: 63–69.
64. Seifert L, Orth D, Button C, et al. An ecological dynamics framework for the acquisition of perceptual-motor skills in climbing. In: Feletti F (ed.) *Extreme sports medicine*. Cham, Switzerland: Springer International Publishing, 2016, pp.365–382.
65. Nabavinik M and Abdolzadeh H. Moderate movement variability is optimal in massive practiced dart throws. *Pedagogy Phys Cult Sports* 2020; 24: 297–302.
66. Arutyunyan GA, Gurfinkel VS and Mirskii ML. Organization of movements on execution by man of an exact postural task. *Biophysics (Oxf)* 1969; 14: 1162–1167.
67. Tversky A and Kahneman D. Judgment under uncertainty: heuristics and biases biases in judgments reveal some heuristics of thinking under uncertainty. *Sci* 1974; 185: 1124–1131.

68. Target Shooting New Zealand. L2 - Rifle Shooting - Theory, https://tsnz.nz/international/issf (accessed 19 February 2025).
69. Reinkemeier H, Bühlmann G, Eckhardt M, et al. Air Rifle Shooting. MEC High Tech Shooting Equipment, 2006.
70. Correia V, Araujo D, Craig C, et al. Prospective information for pass decisional behavior in rugby union. *Hum Mov Sci* 2011; 30: 984–997.
71. McCosker C, Renshaw I, Russell S, et al. The role of elite coaches' expertise in identifying key constraints on long jump performance: how practice task designs can enhance athlete self-regulation in competition. *Qual Res Sport Exerc Health* 2021; 13: 283–299.
72. Seifert L and Intentions DK. Intentions, perceptions and actions constrain functional intra- and inter-individual variability in the acquisition of expertise in individual sports. *Open Sports Sci J* 2012; 5: 68–75.
73. Williams AM, Janelle CM and Davids K. Constraints on the search for visual information in sport. *Int J Sport Exerc Psychol* 2004; 2: 301–318.
74. Ingold T. *Anthropology and/as education*. 1st ed. Book. London:. Routledge, 2018.
75. Wojciechowski P and Wojtowicz K. Challenges in designing measurement systems for formula one cars. In: *2023 IEEE international workshop on metrology for automotive, MetroAutomotive*, Modena, Italy, 2023, pp.57–61. New York, NY, United States: IEEE.
76. Wisbey B, Montgomery PG, Pyne DB, et al. Quantifying movement demands of AFL football using GPS tracking. *J Sci Med Sport* 2010; 13: 531–536.
77. Kelso JAS. *Dynamic patterns : the self-organization of brain and behavior*. Book, Cambridge, Mass: MIT Press, 1995.