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Task-to-run transition stability in standardized
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Abstract

Background: Standardized hybrid fitness racing requires athletes to alternate repeatedly between running and functional exercise tasks. Unlike continuous endurance events, performance in this format depends not only on running speed or station completion time, but also on how well athletes maintain subsequent running performance after each functional task. However, large-scale field evidence describing how the next running split changes after different fixed stations remains limited. We aimed to characterize task-to-run transition stability in a standardized running-focused hybrid fitness racing format using real-world competition split records.

Methods: We conducted a retrospective field-based performance analysis of publicly available competition split records from 132 races held in 2024–2025. The dataset included 13,618 athlete-event result records and was reconstructed into 95,326 station-to-run transition-level observations across seven fixed transitions, from SkiErg → Run 2 to Sandbag Lunges → Run 8. The primary outcome was Δ run, defined as the subsequent running split minus the preceding running split. We described observed Δ run patterns, estimated adjusted station-position differences controlling for previous running split, performance percentile, sex, age group, division, and event fixed effects, and calculated expected–observed residuals to identify transition-specific deviations from model-expected subsequent running performance.

Results: Subsequent running performance differed across the seven fixed station-to-run transitions. In observed analyses, Sandbag Lunges → Run 8 showed the

largest median Δrun (+20 s), followed by Sled Push $\rightarrow$ Run 3 (+14 s), whereas Row $\rightarrow$ Run 6 was the only transition with a negative median Δrun (-4 s). After covariate adjustment, Sandbag Lunges $\rightarrow$ Run 8 and Sled Push $\rightarrow$ Run 3 remained among the transitions with larger subsequent running changes, whereas Row $\rightarrow$ Run 6 remained lower. Residual analyses showed slower-than-expected subsequent running after Sandbag Lunges $\rightarrow$ Run 8 (+9.4 s) and Sled Push $\rightarrow$ Run 3 (+5.5 s), and faster-than-expected subsequent running after Row $\rightarrow$ Run 6 (-9.3 s) and Farmers Carry $\rightarrow$ Run 7 (-6.6 s). These directional patterns were consistent across sex, event year, Pro-only, and relaxed quality-control analyses. **Conclusions:** Subsequent running performance in standardized hybrid fitness racing did not follow a simple linear late-race slowing pattern. Instead, it varied across fixed station-to-run transitions, with larger disruptions after selected lower-limb loading stations and lower-than-expected disruption after Row and Farmers Carry. These findings support task-to-run transition stability as a field-based performance-analysis construct for describing how athletes maintain subsequent running performance after functional tasks in running-focused hybrid fitness racing.

Keywords: hybrid fitness racing; task-to-run transition stability; field-based performance analysis; competition split records; running performance; performance analysis; retrospective observational study

1 Background

Standardized hybrid fitness racing combines repeated running segments with functional exercise tasks performed in a fixed sequence. This structure differs from continuous endurance events, such as road running or cycling, because running performance is repeatedly interrupted by non-running tasks that may alter the athlete's ability to re-establish pace. In this setting, performance is not captured fully by total finish time, running speed, or station completion time alone. It also depends on how well athletes maintain or regain subsequent running performance after each functional task. Pacing research emphasizes that competition performance should be interpreted as a dynamic process of effort distribution and speed regulation across the event [1–4]. Related work on durability and performance fatigability further suggests that the ability to maintain performance under sustained or repeated load may represent an important performance dimension beyond fresh-state capacity [5–8]. We refer to the post-task deviation in

subsequent running performance as a task-to-run performance carryover pattern, and we define the degree to which athletes maintain or regain expected subsequent running performance as task-to-run transition stability.

Several research areas provide relevant background for this question. Concurrent training and strength–endurance interference studies suggest that preceding strength or resistance exercise may be associated with changes in subsequent endurance performance [9–13]. Multimodal transition research, particularly studies of the cycle-to-run transition in triathlon, also shows that a preceding exercise mode can influence subsequent running biomechanics, physiology, and performance [14–17]. However, much of this evidence comes from continuous endurance sports, laboratory-controlled protocols, training-order studies, or single-task transition settings. In standardized hybrid fitness racing, running is interrupted repeatedly by multiple functional tasks within the same competition. Whether these repeated task-to-run transitions show station-specific patterns in subsequent running performance under real-world race conditions remains unclear.

HYROX provides a standardized competition format for examining this problem. The format consists of eight 1-km running segments alternated with eight functional stations performed in a fixed order [18,19]. Existing studies of this format and related hybrid competitions indicate that it is running-focused, high intensity, and characterized by repeated transitions between locomotor and functional exercise demands [20–23]. In the present study, we use this format not as an isolated event-specific case, but as a standardized field model of running-focused hybrid fitness racing. Its fixed sequence and publicly available split records make it possible to compare subsequent running performance after seven fixed station-to-run transitions.

Research on hybrid fitness racing and high-intensity functional training has grown in recent years. Existing work has mainly examined acute physiological responses, performance determinants, athlete profiles, fitness characteristics, station times, pacing

139 strategies, and overall workload patterns [20–28]. These studies show that multimodal
140 competition performance cannot be understood solely from total finish time or aggregate
141 workload. However, to our knowledge, no large-scale field study has systematically
142 examined how the next 1-km running split changes after each fixed functional station in
143 this standardized race structure. Key unanswered questions remain: whether subsequent
144 running changes differ across fixed station-to-run transitions; whether these differences
145 simply reflect general late-race slowing; and whether the main patterns are consistent
146 across performance levels, sex, event year, and race contexts.

152 Using real-world competition split records, we therefore examined task-to-run
153 transition stability across seven fixed station-to-run transitions in standardized running-
154 focused hybrid fitness racing. Large-scale field studies using race split records have
155 been used to examine pacing, performance variation, and environmental associations
156 in endurance events, supporting the value of split-record analysis for understanding
157 competition performance in real-world settings [29,30]. Specifically, we asked four
158 questions: first, whether subsequent 1-km running performance differs across fixed
159 station-to-run transitions; second, whether these differences follow a simple late-race
160 slowing pattern or show transition-specific residual deviations; third, whether transition
161 stability differs across performance tiers; and fourth, whether the main patterns remain
162 directionally consistent across sex, event year, Pro-only, quality-control, and event-level
163 sensitivity analyses. Based on prior work on pacing regulation [1–4], strength–endurance
164 interference [9–13], multimodal transition running [14–17], and durability [5–8], we
165 expected subsequent running performance to vary across fixed station-to-run transitions
166 rather than follow a single linear fatigue pattern.

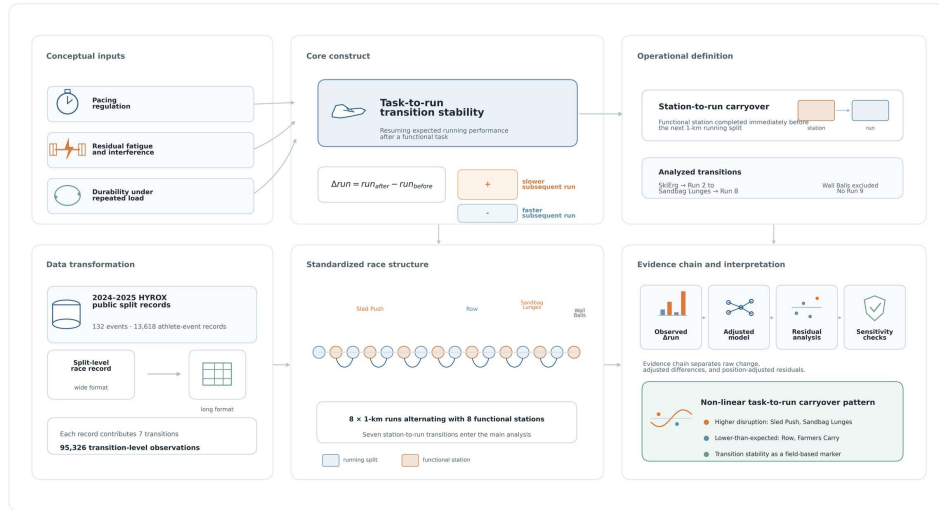


Fig. 1 Conceptual framework and analytical workflow.
 Note. The standardized race format is used as a field-based model of running-focused hybrid fitness racing. The workflow links conceptual inputs, split-level data transformation, the standardized race structure, the operational definition of station-to-run transition stability, and the evidence chain used to interpret task-to-run transition stability.

2 Methods

2.1 Study design and data source

We conducted a retrospective field-based performance analysis using real-world competition split records. We extracted publicly available official split results from a standardized, running-focused hybrid fitness racing format and reconstructed them into athlete-event result records and station-to-run transition-level observations.

We defined two analytical levels. The first level was the athlete-event result record rather than the unique athlete. Therefore, repeated participations by the same athlete were treated as separate athlete-event records. The second level was the station-to-run transition observation, with each athlete-event record contributing seven fixed transition observations. The parsed dataset included 13,942 records from 2024–2025. After quality control, the main analytic sample included 13,618 athlete-event records

from 132 races and yielded 95,326 transition-level observations. Model estimates were interpreted as adjusted station-position contrasts and directional performance patterns.

2.2 Race structure and station-to-run transitions

The standardized race format consisted of eight 1-km running segments alternated with eight functional stations in a fixed order [18,19]. The sequence was Run 1, SkiErg, Run 2, Sled Push, Run 3, Sled Pull, Run 4, Burpee Broad Jump, Run 5, Row, Run 6, Farmers Carry, Run 7, Sandbag Lunges, Run 8, and Wall Balls.

We focused on subsequent running performance after functional task completion. The main analysis therefore included seven fixed station-to-run transitions: SkiErg → Run 2, Sled Push → Run 3, Sled Pull → Run 4, Burpee Broad Jump → Run 5, Row → Run 6, Farmers Carry → Run 7, and Sandbag Lunges → Run 8. Wall Balls was the final functional station and was not followed by a Run 9; therefore, it was not included in the main transition-level analysis and was summarized only as part of the workout-time background information.

Because station identity and race position were fixed within the standardized sequence, all results were interpreted as station-position pair differences rather than isolated station effects.

2.3 Sample construction and quality control

Quality control was used to ensure completeness and plausibility of running splits, functional station splits, and grouping variables. Records were included if they met the following criteria: competition year 2024 or 2025; complete values for all eight running splits and all eight functional station splits; all 1-km running splits within the main plausible range of 120–900 s; positive total finish time; and nonmissing values for sex, age group, division, and race name.

The quality-control flow was as follows. The parsed dataset included 13,942 records from 2024–2025. All records had complete running and functional station splits. After

applying the 120–900 s plausible range for all 1-km running splits, 13,740 records remained. The positive total-time criterion did not exclude additional records. After excluding records with missing grouping variables, the final main analytic sample included 13,618 athlete-event result records, corresponding to a retention rate of 97.7%. The quality-control flow and sample composition are reported in Figure 2, Table 1, Supplementary Figure S1, and Supplementary Table S2.

2.4 Task-to-run variable construction

The original wide-format split records were restructured into a transition-level long format. Each athlete-event record contributed seven station-to-run transition observations. For the transition after the i th functional station, we defined:

$$\Delta run_i = run_{i+1} - run_i$$

where run_i was the 1-km running split immediately before the functional station and run_{i+1} was the 1-km running split immediately after the station. We refer to these variables as run_before and run_after , respectively. Thus, Δrun represented the absolute change in subsequent running time relative to the preceding running segment. Positive values indicated slower subsequent running, and negative values indicated faster subsequent running.

We also calculated a relative change metric:

$$\Delta pct_i = ((run_{i+1} - run_i) / run_i) \times 100$$

where Δpct represented the percentage change in subsequent running time relative to the preceding running split. This metric was used to assess whether the main findings were consistent when running changes were expressed on a relative scale.

Each transition-level observation included the preceding functional station, station position, station-position pair label, run_before , run_after , Δrun , and Δpct .

323 In this study, task-to-run transition stability was described through two complementary
324 dimensions: the central deviation of post-task running from the preceding or model-
325 expected running split, and the dispersion of these changes within each transition.
326
327 The first dimension was represented by `delta_run`, adjusted mean `delta_run`, and
328 position-adjusted residuals. The second dimension was described using interquartile
329 ranges, stratified distributions, and sensitivity analyses. Thus, task-to-run performance
330 carryover was defined as an observed performance pattern derived from split records,
331 not as an isolated physiological effect of a single station.
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337 2.5 Performance tiers and grouping variables

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339 To examine whether task-to-run transition patterns differed by performance level, we
340 calculated performance percentile and performance tier using total finish time. Because
341 total time is not directly comparable across events, sex categories, and divisions,
342 performance percentile was calculated within each event $\times$ sex $\times$ division stratum.
343
344 Lower total time indicated better performance.
345
346
347

348 Athlete-event records were categorized into four performance tiers: Top 10%, 11–
349 50%, 51–75%, and Bottom 25%. Top 10% represented the fastest records within the
350 corresponding event $\times$ sex $\times$ division stratum, whereas Bottom 25% represented the
351 slowest quartile. These tiers were used to examine whether transition stability differed
352 across performance levels.
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356 Other grouping variables included event year, sex, age group, division, and race
357 name. Race name was included as an event fixed effect in the adjusted and residual
358 models.
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362 2.6 Descriptive task-to-run analysis

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364 The first step described observed running changes after each of the seven fixed station-to-
365 run transitions. For each station-position pair, we summarized `run_before`, `run_after`,
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delta_run, and delta_pct using medians, interquartile ranges, means, standard deviations, and bootstrap 95% confidence intervals [36]. This step was used to characterize the raw distribution, median ordering, and magnitude of post-task running changes. Adjusted comparisons were performed in the station-position model described below.

We also summarized observed patterns by sex, event year, division, age group, and performance tier to assess directional consistency across subgroups. Observed descriptive results are reported in Figure 3, Table 2, and Supplementary Table S3. Stratified descriptive results are reported in Figure 6, Figure 7, Supplementary Figure S4, and Supplementary Table S4. This section reports unadjusted descriptive patterns; overall statistical support and covariate-adjusted station-position comparisons are provided by the adjusted model.

2.7 Adjusted station-position model

The second step examined whether differences across station-position pairs remained after accounting for preceding running performance, overall performance level, grouping variables, and event-level differences. Because transition observations were nested within athlete-event records, we interpreted model results as transition-level adjusted descriptive contrasts rather than individual-level causal estimates.

We modeled delta_run as the outcome:

$$\Delta\text{run} \sim \text{station_position_pair} + \text{run_before} + \text{performance_percentile} + \text{sex} + \text{age_group} + \text{division} + \text{event fixed effects}$$

The main predictor was station_position_pair. run_before accounted for the immediately preceding running split. performance_percentile accounted for relative performance level within the event $\times$ sex $\times$ division stratum. Sex, age group, and division were included as grouping covariates. Race name was included as an event fixed effect to account for event-level differences such as venue, timing, implementation conditions, and other unmeasured event-specific factors [37,38].

Model results were reported as adjusted mean `delta_run` for each station-position pair. Sled Pull → Run 4 was used as the reference transition for planned contrasts. Model-based p values were used to describe statistical uncertainty for these planned contrasts under the specified model and were not interpreted as causal evidence. All model estimates were interpreted as station-position pair differences within the standardized sequence.

As a scaling sensitivity analysis, we repeated the same model structure using `delta_pct` as the outcome. Adjusted model results are reported in Figure 4, Table 3, and Supplementary Table S5.

2.8 Expected–observed residual analysis

The third step used expected–observed residual analysis to distinguish general race-position-related slowing from station-position-specific deviations. We first modeled `run_after` as the outcome. The expected-run model included previous running split, linear station position, performance percentile, sex, age group, division, and event fixed effects. The model did not explicitly include station identity as a categorical predictor. Therefore, the expected running split represented the model-estimated subsequent running time based on preceding running performance, linear race position, relative performance level, grouping variables, and event-level differences.

We then calculated position-adjusted residuals:

$$residual = observedrun_after - expectedrun_after$$

Positive residuals indicated that the observed subsequent running split was slower than model expectation, whereas negative residuals indicated that it was faster than model expectation. This analysis was used to characterize whether observed subsequent running performance at each fixed transition deviated from the pattern expected from general race position, previous running performance, performance level, and event-level

differences. Residuals were not interpreted as counterfactual station effects; negative residuals were interpreted as faster-than-expected performance relative to the model, not as evidence that a station improved subsequent running performance. Residual results are reported in Figure 5, Table 4, and Supplementary Table S5.

2.9 Subgroup and sensitivity analyses

We performed several subgroup and sensitivity analyses to assess the robustness of the main task-to-run transition patterns. First, we summarized median `delta_run` by sex and event year. Second, because the sample was predominantly composed of Pro-division records, we repeated the descriptive analysis in the Pro-only subset. Third, we conducted a relaxed quality-control sensitivity analysis by widening the plausible range for 1-km running splits from 120–900 s to 120–1200 s. Fourth, we examined whether the main patterns were consistent when subsequent running changes were expressed using the relative metric `delta_pct`. Fifth, we summarized transition patterns across the four performance tiers.

Finally, we conducted an event-level robustness analysis. This analysis was restricted to events with at least 30 athlete-event result records. For each eligible event, we calculated the event-level median `delta_run` for each of the seven station-position pairs and ranked transitions within each event. We then summarized the proportion of eligible events in which Sandbag Lunges → Run 8 ranked as the largest disruption, Sled Push → Run 3 ranked within the top two disruptions, and Row → Run 6 ranked as the lowest disruption. Performance-tier results are reported in Figure 6 and Supplementary Table S4. Sex-, year-, Pro-only, relaxed quality-control, relative-scale, and event-level robustness results are reported in Figure 7, Table 5, Supplementary Figures S4–S6, and Supplementary Table S6.

2.10 Software and reproducibility

All data processing, quality control, variable construction, statistical analysis, and visualization were performed in Python. We used pandas for data management and long-format restructuring, NumPy for numerical operations, SciPy for statistical procedures, statsmodels for linear model estimation, and matplotlib for visualization. All figures and tables were generated from exported source data tables to ensure consistency across the main manuscript, supplementary material, and machine-readable supplementary tables. Derived summary datasets supporting the main findings are provided as machine-readable supplementary files. Complete software versions, environment files, and core analysis code will be provided according to data-source terms of use and journal data-sharing policies. If required by the journal, an additional sensitivity analysis using robust standard errors clustered at the athlete-event record level can be provided [37,40].

3 Results

3.1 Analytic sample and transition structure

The parsed dataset included 13,942 athlete-event result records from 2024–2025 standardized hybrid fitness racing competitions. After quality control, the main analytic sample included 13,618 athlete-event result records from 132 races, corresponding to a retention rate of 97.7%. Each record contributed seven fixed station-to-run transition observations, yielding 95,326 transition-level observations (Figure 2; Table 1; Supplementary Figure S1; Supplementary Table S2).

The main analytic sample included 5,115 records from 2024 (37.6%) and 8,503 records from 2025 (62.4%). Men accounted for 7,106 records (52.2%) and women for 6,512 records (47.8%). By division, 13,138 records were from the Pro division (96.5%), 397 from the Open division (2.9%), and 83 from the Elite division (0.6%).

The transition-level analysis included seven fixed station-to-run transitions: SkiErg → Run 2, Sled Push → Run 3, Sled Pull → Run 4, Burpee Broad Jump → Run 5, Row → Run 6, Farmers Carry → Run 7, and Sandbag Lunges → Run 8. Wall Balls was the final functional station and was not followed by a subsequent running split; therefore, it was not included in the main transition-level analysis.

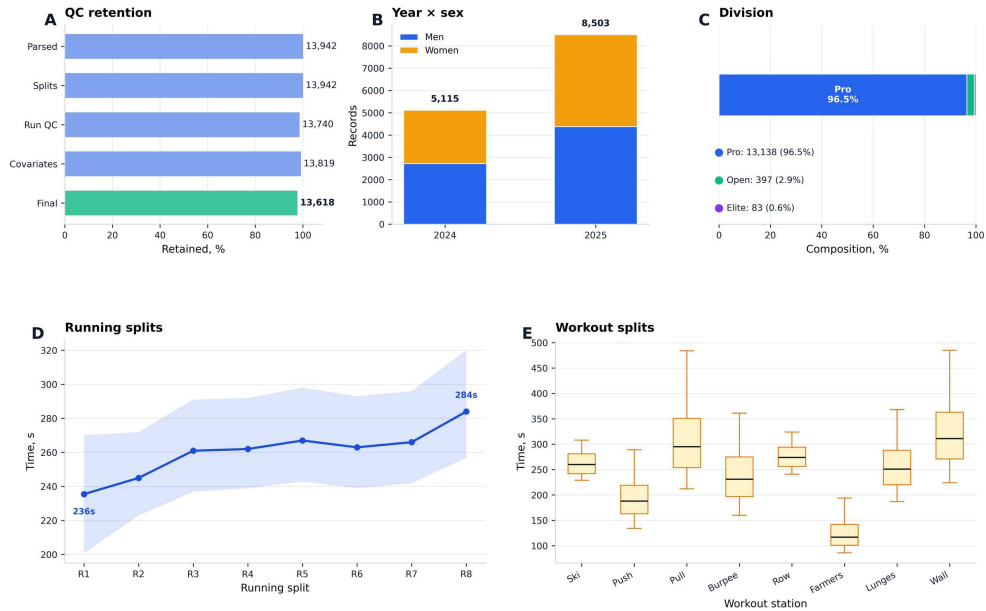


Fig. 2 Data structure and split-level overview. Note. Each athlete-event record contributed seven task-to-run transition observations. Wall Balls is shown as part of the race structure but was excluded from the main transition-level analysis because no subsequent Run 9 followed.

Table 1. Analytic sample characteristics.

Characteristic	Category	n	%
Overall	Athlete-event result records	13618	100
Overall	Events	132	

599				
600	Overall	Transition-level	95326	
601				
602		rows		
603				
604	Event year	2024	5115	37.6
605				
606	Event year	2025	8503	62.4
607				
608	Sex	Men	7106	52.2
609				
610	Sex	Women	6512	47.8
611				
612	Division	Pro	13138	96.5
613				
614	Division	Open	397	2.92
615				
616	Division	Elite	83	0.609
617				
618	Performance tier	Top 10%	1317	9.67
619				
620	Performance tier	11–50%	5464	40.1
621				
622	Performance tier	51–75%	3314	24.3
623				
624	Performance tier	Bottom 25%	3523	25.9

625

626 *Note.* Percentages are calculated among athlete-event result records passing the

627 main quality-control criteria, except for events and transition-level rows.

628

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630 3.2 Observed task-to-run changes across station-position pairs

631

632 Observed median Δrun differed clearly across the seven fixed station-to-run transitions,

633 ranging from -4 s for Row $\rightarrow$ Run 6 to +20 s for Sandbag Lunges $\rightarrow$ Run 8, a

634 span of 24 s (Figure 3; Table 2). This section reports observed, unadjusted patterns;

635 covariate-adjusted station-position contrasts are reported in the adjusted model section.

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638

639 Sandbag Lunges $\rightarrow$ Run 8 showed the largest observed post-task running change,

640 with a median Δrun of +20 s and a median Δpct of +7.6%. Sled Push $\rightarrow$ Run 3 showed

641 the next largest change, with a median Δrun of +14 s and a median Δpct of +6.0%.

642

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644

Burpee Broad Jump → Run 5 and SkiErg → Run 2 both had median Δrun values of +5 s, followed by Farmers Carry → Run 7 (+3 s) and Sled Pull → Run 4 (+2 s).

Row → Run 6 was the only transition with a negative median Δrun , with a median value of -4 s and a median Δpct of -1.5%. The observed ordering did not follow a simple race-position pattern: Sled Push → Run 3 occurred early in the race but showed a relatively large post-task running change, whereas Row → Run 6 occurred later but showed the lowest median Δrun .

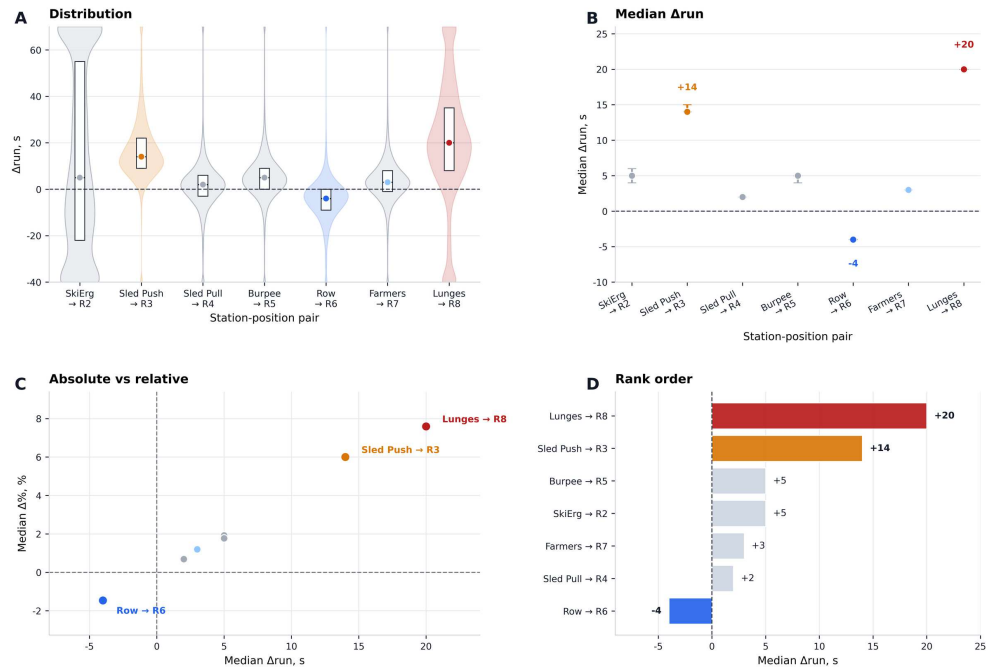


Fig. 3 Observed post-task changes in running performance. Note. Δrun = run_after - run_before. Positive values indicate slower subsequent running. Values are observed and unadjusted. Full numeric summaries are provided in Table 2.

Table 2. Observed task-to-run changes by station-position pair.

Station- position pair	n	Run before median, s	Run after median, s	Median Δ run, s	IQR Δ run, s	Median Δ %, %
SkiErg → Run 2	13618	235.5	245	5	77	1.93
Sled Push → Run 3	13618	245	261	14	13	6
Sled Pull → Run 4	13618	261	262	2	9	0.686
Burpee Broad Jump → Run 5	13618	262	267	5	9	1.77
Row → Run 6	13618	267	263	-4	9	-1.46
Farmers Carry → Run 7	13618	263	266	3	9	1.2
Sandbag Lunges → Run 8	13618	266	284	20	27	7.59

Note. Δ run = run_after - run_before. Positive values indicate slower subsequent running splits. Wall Balls was not included because no subsequent Run 9 followed.

3.3 Adjusted station-position differences

After adjustment for the preceding running split, performance percentile, sex, age group, division, and event fixed effects, differences in subsequent running change remained across station-position pairs (Figure 4; Table 3).

Sandbag Lunges → Run 8 had the highest adjusted mean Δ run (+25.4 s). Relative to the reference transition, Sled Pull → Run 4, the model contrast was +21.6 s (95% CI: 20.9 to 22.2; $p < 0.001$). Sled Push → Run 3 had an adjusted mean Δ run of +10.3 s, with a contrast of +6.5 s relative to Sled Pull → Run 4 (95% CI: 5.9 to 7.1; $p < 0.001$).

Burpee Broad Jump → Run 5 and Farmers Carry → Run 7 had adjusted mean Δ run values of +8.2 s and +7.0 s, respectively. Row → Run 6 had an adjusted mean Δ run of +1.5 s and a contrast of -2.4 s relative to Sled Pull → Run 4 (95% CI: -2.8 to -1.9; $p < 0.001$). SkiErg → Run 2 had an adjusted mean Δ run of -0.1 s and a contrast of -4.0 s relative to Sled Pull → Run 4 (95% CI: -4.8 to -3.1; $p < 0.001$).

The adjusted model retained the main directional pattern observed in the descriptive results: Sandbag Lunges → Run 8 and Sled Push → Run 3 remained among the transitions with larger subsequent running changes, whereas Row → Run 6 and SkiErg → Run 2 remained lower.

Table 3. Adjusted task-to-run model estimates.

Station- position pair	Adjusted mean Δ run, s	Contrast vs Sled Pull, s	Contrast 95% CI	p
SkiErg → Run 2	-0.142	-3.99	-4.8, -3.1	<0.001
Sled Push → Run 3	10.3	6.49	5.9, 7.1	<0.001

783					
784	Sled Pull →	3.84			Reference
785					
786	Run 4				
787					
788	Burpee Broad	8.19	4.35	3.9, 4.8	<0.001
789	Jump → Run 5				
790					
791	Row → Run 6	1.47	-2.37	-2.8, -1.9	<0.001
792					
793	Farmers Carry	6.97	3.12	2.7, 3.5	<0.001
794					
795	→ Run 7				
796					
797	Sandbag	25.4	21.6	20.9, 22.2	<0.001
798					
799	Lunges → Run				
800	8				
801					

802

803 *Note.* Models adjusted for previous running split, performance percentile, sex, age

804 group, division, and event fixed effects. Contrasts are relative to Sled Pull → Run 4. P

805 values are model-based values for planned contrasts and were not adjusted for multiple

806 comparisons; they should not be interpreted as causal evidence.

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811 3.4 Expected–observed residual patterns

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813 The expected–observed residual analysis examined whether observed subsequent run-

814 ning performance deviated from model-expected running time based on previous

815 running split, linear race position, performance percentile, sex, age group, division,

816 and event fixed effects. Positive residuals indicated slower-than-expected subsequent

817 running, whereas negative residuals indicated faster-than-expected subsequent running

818 (Figure 5; Table 4).

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823 Sandbag Lunges → Run 8 and Sled Push → Run 3 were the main positive-residual

824 transitions. Sandbag Lunges → Run 8 had a median residual of +9.4 s (95% CI: 9.0

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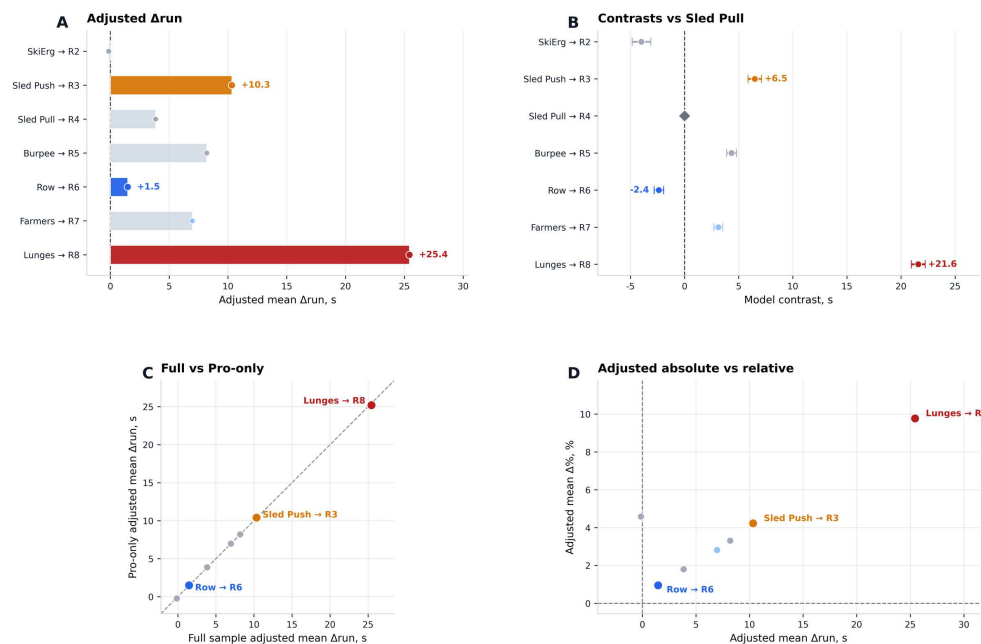


Fig. 4 Adjusted task-to-run transition patterns.

Note. Adjusted estimates are based on models controlling for previous running split, performance percentile, sex, age group, division, and event fixed effects. Estimates are interpreted as station-position pair differences. Model contrasts are relative to Sled Pull → Run 4.

to 9.9), and Sled Push → Run 3 had a median residual of +5.5 s (95% CI: 5.2 to 5.8). Both transitions showed slower-than-expected subsequent running.

Row → Run 6 and Farmers Carry → Run 7 showed negative residuals. Row → Run 6 had the lowest median residual across all transitions (-9.3 s; 95% CI: -9.5 to -9.0). Farmers Carry → Run 7 had a median residual of -6.6 s (95% CI: -6.9 to -6.4). These negative residuals indicated that observed subsequent running times were lower than model expectations at these transitions.

Other transitions had median residuals of -4.0 s for SkiErg → Run 2, -2.2 s for Sled Pull → Run 4, and -0.5 s for Burpee Broad Jump → Run 5. The residual trajectory did not increase monotonically with race position. Sled Push → Run 3 showed a positive residual early in the race, Row → Run 6 and Farmers Carry → Run 7 showed

negative residuals in the middle-to-late portion of the race, and Sandbag Lunges → Run 8 again showed a positive residual late in the race.

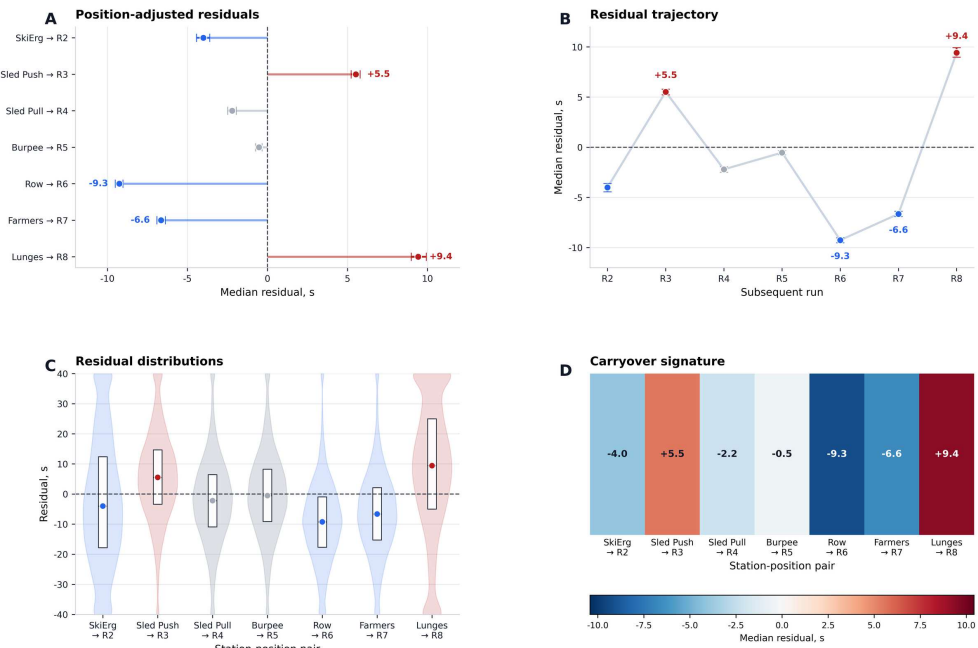


Fig. 5 Expected-observed residual patterns. Note. Residual = observed subsequent running split - expected subsequent running split. Positive residuals indicate slower-than-expected running, and negative residuals indicate faster-than-expected running. Negative residuals should not be interpreted as beneficial causal effects. Error bars indicate bootstrap 95% confidence intervals where shown.

Table 4. Expected-observed residual patterns.

Station-position pair	n	Median residual, s	Residual 95% CI	Q1, s	Q3, s	Interpretation
SkiErg → Run 2	13618	-4.01	-4.4, -3.6	-17.9	12.4	Faster than expected
Sled Push → Run 3	13618	5.52	5.2, 5.8	-3.4	14.7	Slower than expected
Sled Pull → Run 4	13618	-2.2	-2.5, -1.9	-10.9	6.4	Faster than expected
Burpee Broad Jump → Run 5	13618	-0.533	-0.7, -0.3	-9.17	8.25	Near expected
Row → Run 6	13618	-9.26	-9.5, -9.0	-17.7	-0.951	Faster than expected

Station-position pair	n	Median residual, s	Residual 95% CI	Q1, s	Q3, s	Interpretation
Farmers Carry → Run 7	13618	-6.65	-6.9, -6.4	-15.3	2.09	Faster than expected
Sandbag Lunges → Run 8	13618	9.42	9.0, 9.9	-5.02	25.0	Slower than expected

Note. Residual = observed subsequent running split - expected subsequent running split. Expected running was estimated from previous_run, linear station_position, performance_percentile, sex, age_group, division, and event fixed effects without explicitly encoding station_before. Positive residuals indicate slower-than-expected running; negative residuals indicate faster-than-expected running and do not imply causal facilitation.

3.5 Performance-tier differences

Task-to-run transition patterns differed across performance tiers, with the largest tier differences concentrated at selected transitions (Figure 6; Table 5; Supplementary Table S4). In the Top 10% tier, median Δrun was +11 s for Sled Push → Run 3 and +16 s for Sandbag Lunges → Run 8. In the Bottom 25% tier, the corresponding values were +17 s and +24 s. The differences between the Bottom 25% and Top 10% tiers were approximately 6 s for Sled Push → Run 3 and 8 s for Sandbag Lunges → Run 8.

SkiErg → Run 2 also showed a clear performance-tier difference. Median Δrun for SkiErg → Run 2 was +2 s in the Top 10% tier and +9 s in the Bottom 25% tier, a difference of approximately 7 s. In contrast, Burpee Broad Jump → Run 5, Sled Pull → Run 4, and Farmers Carry → Run 7 showed smaller differences between the Bottom 25% and Top 10% tiers, each approximately 1 s. Row → Run 6 remained low or negative across tiers, with median Δrun values of -3 s in the Top 10% tier and -4 s in the Bottom 25% tier.

Overall, performance-tier differences were not distributed evenly across all transitions. They were concentrated primarily at Sled Push → Run 3, Sandbag Lunges → Run 8, and SkiErg → Run 2.

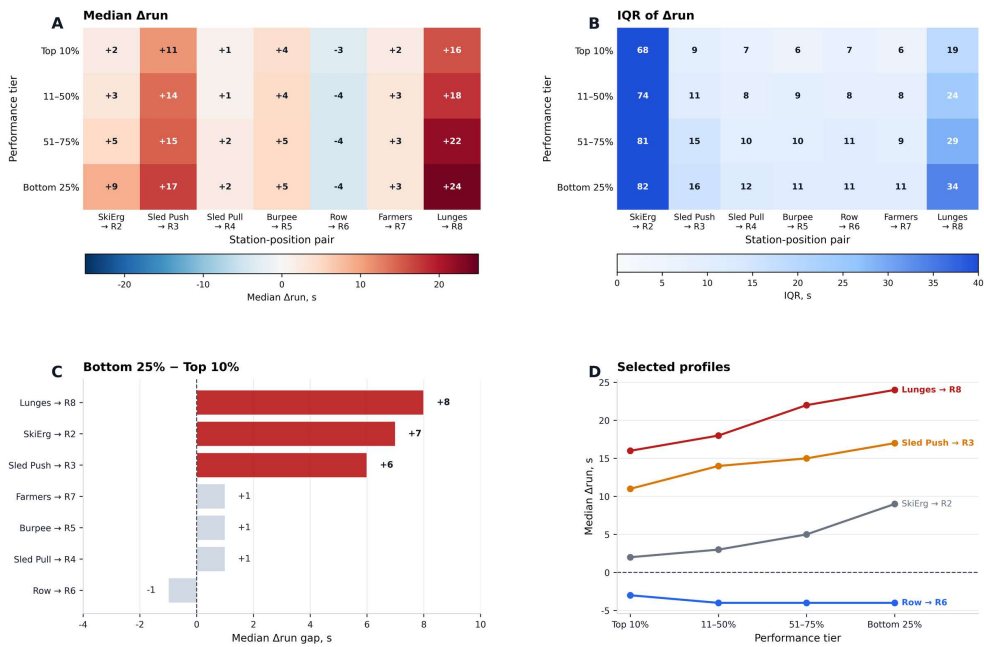


Fig. 6 Performance-tier transition patterns. Note. Performance tiers were defined within event $\times$ sex $\times$ division strata. Positive Δ run values indicate slower subsequent running. Larger dispersion is interpreted as lower descriptive task-to-run transition stability, not as a direct measure of an individual physiological trait.

3.6 Subgroup and sensitivity analyses

Subgroup and sensitivity analyses examined whether the main transition patterns depended on sex, event year, division composition, or quality-control thresholds. Overall, the main directional patterns were consistent across sex-stratified, year-stratified, Pro-only, and relaxed quality-control analyses (Figure 7; Table 5; Supplementary Figure S5; Supplementary Table S6).

In the full sample, median Δrun values for Sled Push $\rightarrow$ Run 3, Row $\rightarrow$ Run 6, and Sandbag Lunges $\rightarrow$ Run 8 were +14 s, -4 s, and +20 s, respectively. In men, the corresponding values were +14 s, -4 s, and +20 s; in women, they were +15 s, -4 s, and +20 s. By event year, the corresponding values were +16 s, -4 s, and +22 s in 2024, and +14 s, -4 s, and +19 s in 2025. In the Pro-only subset, the corresponding median Δrun values were +15 s, -4 s, and +20 s.

In the relaxed quality-control analysis, where the plausible range for 1-km running splits was widened from 120–900 s to 120–1200 s, median Δrun values for Sled Push $\rightarrow$ Run 3, Row $\rightarrow$ Run 6, and Sandbag Lunges $\rightarrow$ Run 8 were +14.5 s, -4 s, and +20 s, respectively. Analyses using the relative change metric, Δpct , showed the same directional pattern as the absolute time-based analyses (Supplementary Figure S5).

Event-level analyses showed that the main patterns were not driven entirely by a small number of events, although event-level heterogeneity was present (Supplementary Figure S6; Supplementary Table S6). Among eligible events with at least 30 athlete-event result records, Sled Push $\rightarrow$ Run 3 ranked within the top two disruption transitions in 78.3% of events (101/129), Row $\rightarrow$ Run 6 ranked as the lowest disruption transition in 45.0% of events (58/129), and Sandbag Lunges $\rightarrow$ Run 8 ranked as the largest disruption transition in 43.4% of events (56/129).

Across analyses, Sled Push $\rightarrow$ Run 3 and Sandbag Lunges $\rightarrow$ Run 8 generally remained among the transitions with larger subsequent running changes, whereas Row $\rightarrow$ Run 6 remained low or negative. The main pattern was directionally consistent across subgroup and sensitivity analyses, with observable heterogeneity at the event level.

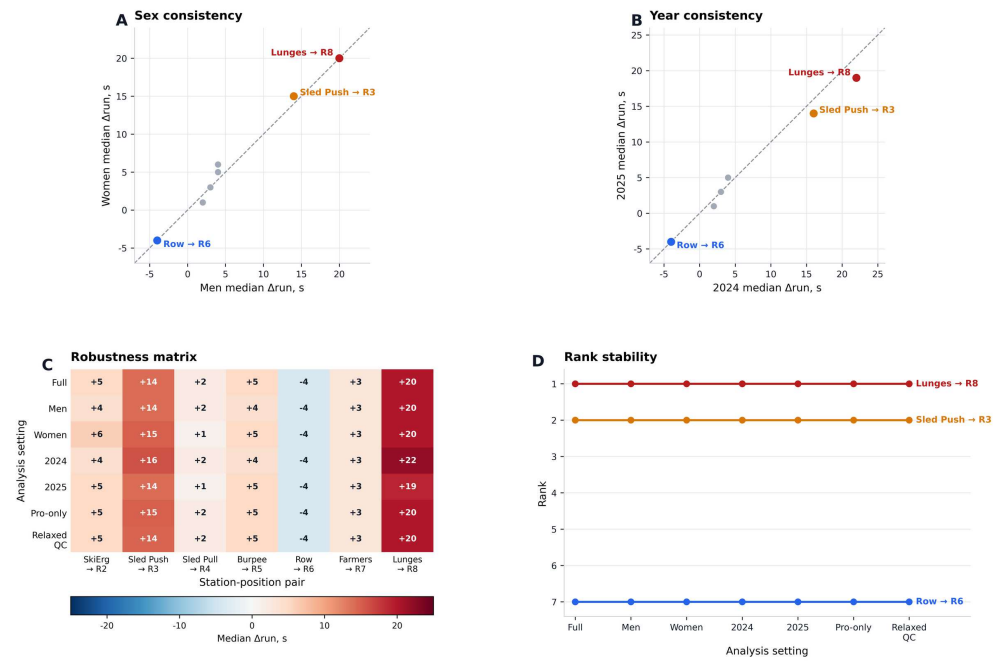


Fig. 7 Subgroup consistency and robustness. Note. Panels compare directional consistency across sex, year, Pro-only, relaxed quality-control, relative-scale, and event-level analyses. Positive values indicate slower subsequent running. Event-level summaries are restricted to eligible events with at least 30 athlete-event records.

Table 5. Subgroup and sensitivity summary.

Analysis setting	Sled Push	Row	→	Lunges	→	Pattern summary
	→	R3 R6	Δrun,	R8	Δrun,	
	Δrun, s	s		s		
Full sample	14	-4		20		Sled Push elevated; Lunges elevated; Row low/negative
Men	14	-4		20		Sled Push elevated; Lunges elevated; Row low/negative
Women	15	-4		20		Sled Push elevated; Lunges elevated; Row low/negative
2024	16	-4		22		Sled Push elevated; Lunges elevated; Row low/negative
2025	14	-4		19		Sled Push elevated; Lunges elevated; Row low/negative
Pro-only	15	-4		20		Sled Push elevated; Lunges elevated; Row low/negative
Relaxed QC	14.5	-4		20		Sled Push elevated; Lunges elevated; Row low/negative
Top 10%	11	-3		16		Sled Push elevated; Lunges elevated; Row low/negative
Bottom 25%	17	-4		24		Sled Push elevated; Lunges elevated; Row low/negative
Event-level eligible events						Event-level: Lunges ranked 1st: 43.4% (56/129); Event-level: Sled Push ranked top 2: 78.3% (101/129); Event-level: Row ranked 7th: 45.0% (58/129)

Note. Values are median Δrun estimates for three key station-position pairs across subgroup and sensitivity analyses. Performance-tier rows summarize Supplementary Table S4; sex, year, Pro-only, relaxed quality-control, and event-level rows summarize Supplementary Table S6. Event-level metrics summarize the proportion of eligible events in which the specified descriptive rank criterion was met.

1151 4 Discussion

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1154 4.1 Principal findings

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1156 We analyzed real-world competition split records from a standardized hybrid fitness
1157 racing format and examined subsequent 1-km running performance after seven fixed
1158 station-to-run transitions. The main finding was that subsequent running performance
1159 did not follow a simple linear late-race slowing pattern. Instead, post-task running
1160 changes varied across fixed transitions. Larger running disruptions were observed after
1161 Sandbag Lunges → Run 8 and Sled Push → Run 3, whereas Row → Run 6 and
1162 Farmers Carry → Run 7 were faster than model expectations.

1167 This pattern indicates that subsequent running performance in hybrid fitness racing
1168 is not merely a by-product of accumulated race fatigue. If post-task running changes
1169 primarily reflected monotonic late-race slowing, residuals would be expected to increase
1170 broadly with race position. Instead, Sled Push → Run 3 showed slower-than-expected
1171 subsequent running early in the race, whereas Row → Run 6 and Farmers Carry →
1172 Run 7 showed faster-than-expected subsequent running in the middle-to-late portion
1173 of the race. These findings are consistent with pacing research that views competition
1174 performance as a dynamic process of effort regulation [1–4] and with work on durability
1175 and performance fatigability showing that performance maintenance under repeated
1176 load is not necessarily linear [5–8].

1184 The contribution of this study is not simply to identify which station was followed
1185 by slower running. Rather, we provide a transition-level performance framework for
1186 describing how subsequent running performance changes after fixed functional tasks
1187 in a standardized running–functional task sequence. This framework extends hybrid
1188 fitness racing analysis beyond total finish time, total running time, or individual station
1189 time toward the structure of task-to-run transitions [20–23,29,30].

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4.2 Task-to-run transition stability as a field-based construct 1197

We conceptualized task-to-run transition stability as the degree to which athletes maintain or regain expected subsequent running performance after completing a functional task. We operationalized this construct through two complementary dimensions: the central deviation of post-task running from the preceding or model-expected running split, and the dispersion of these changes within each transition. The first dimension was captured by Δ_{run} , adjusted mean Δ_{run} , and expected–observed residuals. The second was described using interquartile ranges, stratified distributions, and sensitivity analyses. 1198
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This construct complements conventional performance metrics. Total finish time, total running time, and station time describe overall race performance, but they do not directly show whether athletes maintain subsequent running performance after functional tasks. In a competition format with repeated alternation between running and functional stations, the first running segment after each task provides a distinct performance signal. Task-to-run transition stability therefore offers a field-based way to quantify how running performance is maintained after task-specific demands. 1212
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The present data show that this construct can be quantified from competition split records. Observed Δ_{run} described direct changes from the preceding to the subsequent running split. Adjusted station-position models showed that transition differences remained after accounting for previous running performance, relative performance level, grouping variables, and event fixed effects. Expected–observed residuals further showed which transitions deviated from the pattern expected from general race position and athlete-event characteristics. Together, these analyses support task-to-run transition stability as an operational performance dimension in running-focused hybrid fitness racing [5–8,31–34]. 1224
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1243 4.3 Performance interpretation of transition-specific patterns

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1245 The observed transition ordering is consistent with a task-specific performance inter-
1246 pretation. Sled Push and Sandbag Lunges involve substantial lower-limb loading,
1248 propulsion, or muscular endurance demands, and both were followed by larger dis-
1249 ruptions in subsequent running. Strength–endurance interference and acute residual
1250 fatigue research provide relevant background for interpreting larger running changes
1251 after high-load lower-limb tasks [9–13]. In contrast, Row is performed in a seated
1252 position and involves substantial upper-body and trunk contribution, whereas Farmers
1253 Carry involves loaded forward locomotion with a movement rhythm that remains direc-
1254 tionally aligned with subsequent running. The lower or negative residuals after these
1255 transitions are therefore more plausibly interpreted through differences in task-to-run
1256 movement transitions than through race position alone [14–17]. Research on running
1257 economy and running biomechanics provides additional background for interpreting
1258 how movement demands may relate to subsequent running performance [31,32].

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1267 These findings also show that the difficulty of a functional station and its effect on
1268 the next running segment are not necessarily equivalent. A station may be demanding
1269 in terms of cardiovascular load, muscular endurance, or completion time, yet its
1270 subsequent running pattern may depend on movement mode, lower-limb loading, pacing
1271 disruption, and the athlete’s ability to reorganize running mechanics immediately after
1272 task completion. The Row → Run 6 pattern shows that a later race position does not
1273 necessarily correspond to greater running disruption. Conversely, the Sled Push → Run
1274 3 pattern shows that substantial task-to-run disruption can occur early in the race.

1275 The performance patterns observed here provide clear targets for future mechanis-
1276 tic studies. Strength–endurance interference and residual fatigue research support the
1277 interpretation of larger disruptions after high-load lower-limb transitions [9–13]; multi-
1278 modal transition studies provide a reference for interpreting task-to-run movement
1279 changes [14–17]; and work on running economy, biomechanics, and eccentric muscle
1280 changes [14–17]; and work on running economy, biomechanics, and eccentric muscle
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actions provides relevant background for linking movement demands to subsequent running performance [31–35]. The present study identifies where these mechanisms may be most worth testing in future studies that combine competition split records with physiological, biomechanical, neuromuscular, or wearable-derived measures.

4.4 Practical implications

Performance-tier analyses showed that differences between higher- and lower-performing athlete-event records were concentrated at selected transitions rather than distributed evenly across the race. The Bottom 25% and Top 10% tiers differed most clearly after Sled Push → Run 3, Sandbag Lunges → Run 8, and SkiErg → Run 2, whereas Row → Run 6 remained low or negative across tiers. This suggests that performance gaps in hybrid fitness racing may be expressed disproportionately at specific task-to-run transitions rather than as uniform slowing across all running segments.

These findings have practical value for competition review and performance monitoring. Coaches and practitioners can use the first running split after each functional station as a practical checkpoint. A disproportionate slowing after selected stations may indicate that an athlete’s general running ability is not translating effectively under task-specific loading or transition demands. This approach does not replace traditional monitoring of total finish time, running pace, or station completion time; rather, it adds a transition-level view of how well athletes resume running after functional tasks.

Task-to-run transition stability may therefore serve as a supplemental metric for race analysis. It can help identify where running performance is most disrupted and where future training or pacing interventions may be evaluated. The current findings do not prescribe a specific training method. Instead, they provide a data-driven framework for testing whether task-specific transition practice, post-station running control, or race-pacing strategies can improve subsequent running stability in future intervention studies [33,34].

1335 4.5 Strengths, limitations, and future directions

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1337 This study has three main strengths. First, we used a large set of real-world compe-
1338 tition split records and reconstructed 13,618 athlete-event result records into 95,326
1339 station-to-run transition-level observations. This provided sufficient scale to examine
1340 transition-level patterns with high descriptive stability. Second, the standardized race
1341 structure allowed comparisons across seven fixed station-to-run transitions within the
1342 same sequence. Third, we combined observed Δ run, adjusted station-position models,
1343 expected-observed residuals, stratified analyses, relaxed quality control, relative-scale
1344 analyses, and event-level robustness checks to evaluate the directional consistency of
1345 the main patterns.

1352 Several boundaries should be considered when interpreting the findings. First, the
1353 analysis was based on publicly available competition split records. Because station
1354 identity and race position are inherently linked in the standardized format, findings
1355 represent station-position performance contrasts rather than isolated station effects.
1356 Second, the analytical unit was the athlete-event result record rather than the unique
1357 athlete. Repeated participations by the same athlete may therefore appear as separate
1358 records, and the seven transition observations within each record are not fully inde-
1359 pendent. Third, public split records did not include training history, heart rate, blood
1360 lactate, muscle oxygenation, electromyography, gait dynamics, or perceived exertion.
1361 Accordingly, this study characterizes competition performance patterns rather than
1362 direct physiological or biomechanical mechanisms.

1370 Despite these boundaries, the study provides a reproducible field-based framework
1371 for analyzing task-to-run transition stability. Future work can combine competition split
1372 records with wearable sensors, physiological monitoring, biomechanical measurement,
1373 or training interventions to test the mechanisms underlying transition-specific running
1374 disruptions. Such work can also evaluate whether task-to-run transition stability is
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trainable and whether it can support competition review and performance-monitoring practice.

5 Conclusions

In this large-scale field-based performance analysis, subsequent running performance in standardized hybrid fitness racing varied across fixed station-to-run transitions and did not follow a simple linear late-race slowing pattern. Larger disruptions were observed after Sandbag Lunges → Run 8 and Sled Push → Run 3, whereas Row → Run 6 and Farmers Carry → Run 7 were faster than model expectations.

These findings support task-to-run transition stability as a field-based performance-analysis construct in running-focused hybrid fitness racing. This construct describes how well athletes maintain or regain expected subsequent running performance after functional tasks and provides an operational framework for competition review, performance monitoring, and future mechanistic research. Future studies can combine split-record analysis with physiological, biomechanical, wearable, or intervention data to examine the mechanisms and trainability of task-to-run transition stability.

Abbreviations. Δ run: Change in subsequent running split time

Δ pct: Relative change in subsequent running split time

CI: Confidence interval

IQR: Interquartile range

OA: Open access

RPE: Rating of perceived exertion

VO₂: Oxygen uptake

1427 **Declarations**

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1429 **Ethics approval and consent to participate**

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1432 This study used publicly available competition split records and did not involve direct
1433 contact with athletes, experimental intervention, or collection of private health infor-
1434 mation. The analysis was conducted at the athlete-event result-record level using
1435 publicly available performance records. According to the publicly available and ret-
1436 rospective record-based nature of the study, formal ethics approval and individual
1437 informed consent were not required.

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1443 **Consent for publication**

1444

1445 Not applicable.

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1448 **Availability of data and materials**

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1450 The derived summary datasets supporting the main conclusions of this study are
1451 included within the article and its supplementary files. Additional file 1 provides
1452 supplementary methods, figures, and table notes, and Additional file 2 provides machine-
1453 readable supplementary tables. The original competition split results were obtained
1454 from publicly available event result pages and are not owned or controlled by the
1455 authors. Because of source-data terms of use and considerations related to potentially
1456 identifiable athlete-level records, the complete row-level raw dataset is not provided
1457 as a public supplementary file. De-identified analytic data and core analysis code
1458 are available from the corresponding author upon reasonable request, provided that
1459 such sharing is compatible with the source-data terms of use and journal data-sharing
1460 policies.

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1468

1469 **Competing interests**

1470

1471 The authors declare that they have no competing interests.

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analyses, created the figures and tables, interpreted the findings, and drafted the	1483
manuscript. All authors read and approved the final manuscript.	1484
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and tables. Word document. This file includes supplementary methods, quality-control	1502
diagnostics, split-level variable definitions, running and workout split distributions,	1503
stratified analyses, sensitivity analyses, event-level robustness analyses, and full	1504
supplementary table notes.	1505
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Additional file 2. Machine-readable supplementary tables. Excel workbook. This	1509
file includes quality-control flow, variable definitions, descriptive statistics, stratified	1510
results, model estimates, residual summaries, sensitivity analyses, and event-level	1511
robustness results.	1512
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