Statistical Analysis and Results

# 1. Statistical Analysis

The present analysis was not pre-registered as we had no a priori hypotheses and thus was considered exploratory. Inferential statistics were treated as highly unstable local descriptions of the relations between model assumptions and data in order to acknowledge the inherent uncertainty in drawing generalised inferences from single and small samples (Amrhein, Trafimow, et al., 2019). For all analyses we opted to avoid dichotomising the existence of effects and therefore did not employ traditional null hypothesis significance testing on parameter estimates (Amrhein, Greenland, et al., 2019; McShane et al., 2019). Instead, we opted to take an estimation-based approach (Cumming, 2014). For all analyses model parameter estimates and their precision (i.e., 95% confidence intervals [CI]), along with conclusions based upon them, were interpreted continuously and probabilistically, considering data quality, plausibility of effect, and previous literature, all within the context of each model. We focused primarily on qualitative examination of our results based on visualization of the data and models for fixed effects. All analysis was performed in R (version 4.3.3, The R Foundation for Statistical Computing, 2022) and all data and code is presented in the supplementary materials <https://osf.io/ugbtd/>.All data visualisations were made using ggplot2 (Wickham et al., 2022), ggeffects (Lüdecke et al., 2024) and the patchwork (Pedersen, 2022) packages. The aim of our analysis was to explore to explore the effects of both low and high BFR conditions upon physiological and perceptual parameters during the warm-up, and on performance outcomes as a result of the warm-up. Linear mixed effects models were used with Restricted Maximal Likelihood estimation using the lme4 package (Bates et al., 2023). Given the variety of outcomes examined, the timing of their data collection (e.g., pre- to post-warm-up, during warm-up, or post-warm-up only), and the number of measurements taken (e.g., single measures or multiple measures) we describe all of the specific model structures, in addition to model checks and diagnostics using the performance package (Lüdecke (@strengejacke) et al., 2024), in the online supplementary materials (download and view html file from: <https://osf.io/4jtzu>). Where possible we utilised maximal random effects structures for the data (i.e., as long as there were sufficient degrees of freedom, convergence could be achieved, and singularity was avoided).

# 2. Results

Full model summaries including all fixed effect parameter estimates, their confidence intervals, and p values, in addition to all random effect estimates and their correlations, are provided in the online supplementary materials (download and view html file from: <https://osf.io/3bdwt>. Here we focus on presenting the key results for the effects of condition, or condition:time interaction effects (i.e., where timepoint was pre- to post-warm-up or multiple measures where taken during warm-up such as heart rate each minute).

## 2.1 Effects of Warm-up on Physiological and Perceptual Outcomes

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| Figure 1: ADD TEXT. |

### 2.1.1 Heart Rate

On average heart rate was typically higher during the high BFR condition compared with the control condition (beats.minute = 9.64 [95% CI: 3.69, 15.58]), though not clearly so with the low BFR condition (beats.minute = 1.78 [95% CI: -6.12, 9.68]). Heart rate was seen to rise over time (i.e., each minute) in the control condition (beats.minute = 1.31 [95% CI: 0.85, 1.78]), but heart rates were approximately similar by the end of the warmup such that, given it’s higher average heart rate throughout, they rose more slowly during the high BFR condition (Condition [High BFR]:Minute interaction; beats.minute = -0.53 [95% CI: -1.08, 0.02]). Heart rate results are seen in figure ([Figure 1](#fig-warmup) (A)).

### 2.1.2 Blood Lactate

Blood lactate was fit using log transformed values and thus coefficients are given as exponents (i.e., the factor to which a one unit change in the predictor increases or decreases blood lactate). Blood lactate was approximately similar at baseline and increased post warm-up in the control condition by a factor of 2.41 [95% CI: 1.99, 2.91]. There was a tendency for blood lactate to increase from pre to post warmup by a greater degree in both the low BFR (Condition [Low BFR]:Timepoint interaction; 1.09 [95% CI: 0.83, 1.43])) and high BFR conditions (Condition [High BFR]:Timepoint interaction;1.23 [95% CI: 0.94, 1.61]), though interval estimates suggested that a lesser degree of change was also compatible with the model and data. Blood lactate results are seen in figure ([Figure 1](#fig-warmup) (B)).

### 2.1.3 Rating of Perceived Exertion

Rating of perceived exertion under the control condition was 10.85 [95% CI: 10.08, 11.62] points. The low BFR condition resulted in a 1 [95% CI: 0.02, 1.98] points greater rating of perceived exertion compared to the control condition, and the high BFR condition resulted in a 3.55 [95% CI: 2.57, 4.53] points greater rating of percieved exertion. Rating of perceived exertion results are seen in figure ([Figure 1](#fig-warmup) (B)).

## 2.2 Effects of Warm-up on Performance Outcomes

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| Figure 2: ADD TEXT. |

### 2.2.1 Sit and Reach

Sit and reach distance tended to improve for the control condition from pre- to post-warm-up by 1.34 [95% CI: 0.98, 1.71] cm. There was a tendency for improvements from pre- to post-warm-up to be slightly greater in both the low BFR (Condition [Low BFR]:Timepoint interaction; 1.08 [95% CI: -0.46, 2.63])) and high BFR conditions (Condition [High BFR]:Timepoint interaction;0.7 [95% CI: -0.69, 2.09]), though interval estimates suggested that a lesser improvement for these conditions was also compatible with the model and data. Sit and reach results are seen in figure ([Figure 2](#fig-perform) (A)).

### 2.2.2 Countermovement Jump

Compared with the control condition (30.54 [95% CI: 26.94, 34.15] cm) there was a tendency for performance to worse post-warm-up for low BFR (-1.4 [95% CI: -3.31, 0.51] cm) and moreso for high BFR (-2.55 [95% CI: -4.23, -0.87] cm). Countermovement jump results are seen in figure ([Figure 2](#fig-perform) (B)).

### 2.2.3 Sprints

There was essentially no clear effect of either condition compared to the control condition for sprint time, nor any interaction with sprint distance. Sprint time results are seen in figure ([Figure 2](#fig-perform) (C)).

### 2.2.4 Isometric Mid Thigh Pull

Compared with the control condition (2269.8 [95% CI: 1966.2, 2573.4] N) there little impact upon performance post-warm-up for low BFR (3.17 [95% CI: -88.81, 95.14] N) and for high BFR (-11.68 [95% CI: -77.75, 54.39] N). Isometric Mid Thigh Pull results are seen in figure ([Figure 2](#fig-perform) (D)).

# 3. References

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