ESTABLISHING THE NEUROMUSCULAR BENCHMARK: AN UNSUPERVISED MACHINE LEARNING ANALYSIS EXAMINING MUSCLE STRENGTH IN FEMALE ATHLETES

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INTRODUCTION

- Neuromuscular strength benchmarking that includes lower limb maximal strength, leg power output, vertical jump performance, and plyometric ability is used to inform strength training and injury rehabilitation in athletes[1].
- The threshold of strength needed by different athlete populations and the combination of strength characteristics that define performance in various athletes are not well defined[2].
- The expression of neuromuscular strength is complex and influenced by biological, psychological, and social factors, including an athlete's attitude towards strength training[3].
- Moving beyond analyses of normative data in isolated metrics, which have traditionally been used to inform benchmarks, unsupervised machine learning may identify sub-groups of athletes with similar neuromuscular strength characteristics (i.e., profiles)[4].
- **Purpose:** To explore the existence of neuromuscular strength clusters in female university athletes and examine the relationship between neuromuscular strength profiles and attitudes towards strength training.

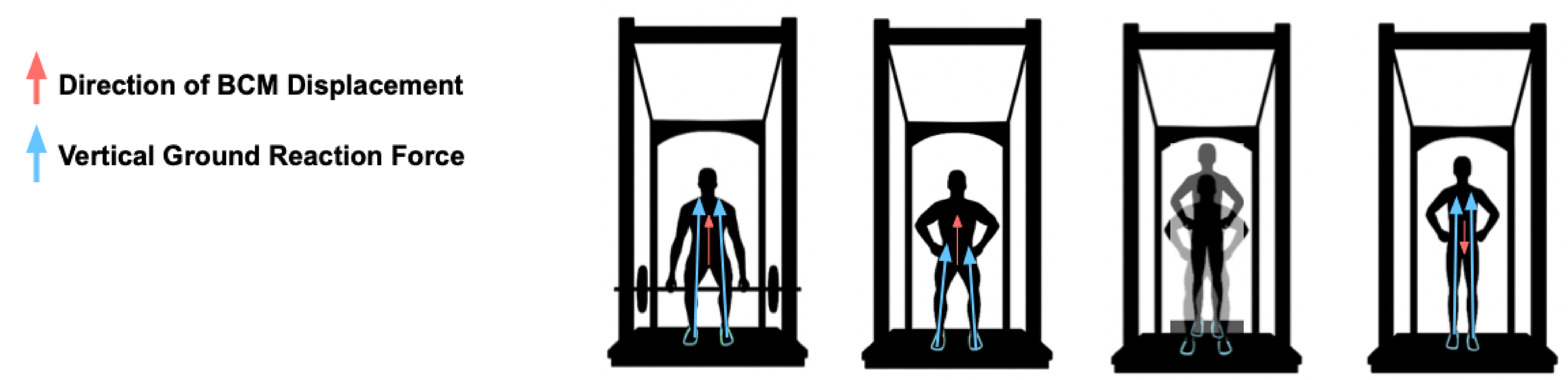
METHODS

- **Participants:** female university athletes (n=192) from six high-risk sports for lower body injury.
- **Baseline Testing:** participants completed neuromuscular strength testing on a dual force plate system comprising: (1) countermovement jump (CMJ) with extra loads corresponding to 0% and 60% body mass; (2) unilateral CMJ testing; (3) unilateral repeat hop testing; (4) isokinetic multi-joint leg press strength testing. Athletes completed a questionnaire to evaluate attitudes towards strength training.
- **Unsupervised Machine Learning:** 39 metrics (e.g., jump height) across 5 testing conditions were selected. Data was scaled, imputed, and UMAP was used for dimensionality reduction. K-means was used for clustering (k=3).
- **Post Hoc Analyses:** Linear regression modelling was used to examine differences in age, body mass, and attitude towards training across clusters.

RESULTS

Table 1: Average CMJ Performance Across Neuromuscular Strength Profiles.

♀ Countermovement Jump	Profile 1	Profile 2	Profile 3
Jump height (cm)	23.8 [4.0]	23.3 [4.7]	29.8 [4.4]
Peak propulsive power (W/kg)	41.9 [4.7]	39.5 [5.3]	47.6 [5.1]
Rate of power development (W/kg/s)	224.2 [58.8]	166.2 [40.4]	247.1 [45.4]
Net eccentric decel impulse (Ns)	63.4 [11.5]	74.1 [17.1]	84.2 [15.9]
Peak Braking power (W/kg)	12.1 [2.7]	12.8 [3.4]	17.5 [4.0]
Concentric phase duration (s)	0.26 [0.03]	0.31 [0.03]	0.26 [0.03]
Eccentric decel phase duration (s)	0.17 [0.03]	0.20 [0.03]	0.15 [0.02]
Contraction time (s)	0.81 [0.10]	0.94 [0.10]	0.82 [0.11]
Eccentric decel stiffness (N/m/kg)	111.9 [41.1]	73.5 [19.4]	118.0 [34.1]
Force at zero velocity (N/kg)	21.0 [2.1]	19.8 [1.9]	23.4 [2.2]
V_{max}-TOV percent difference (%)	7.6 [1.6]	8.1 [1.7]	6.4 [1.5]



	Sport	ACL (n)	Strength	JH/Power	Contraction Time	Stiffness
Profile 1	Mixed	2	Low	Low	Fast	High
Profile 2	Mixed	3	Low	Low	Slow	Low
Profile 3	Mixed	1	High	High	Fast	High

Figure 1: Neuromuscular Strength Profiles Characteristics.

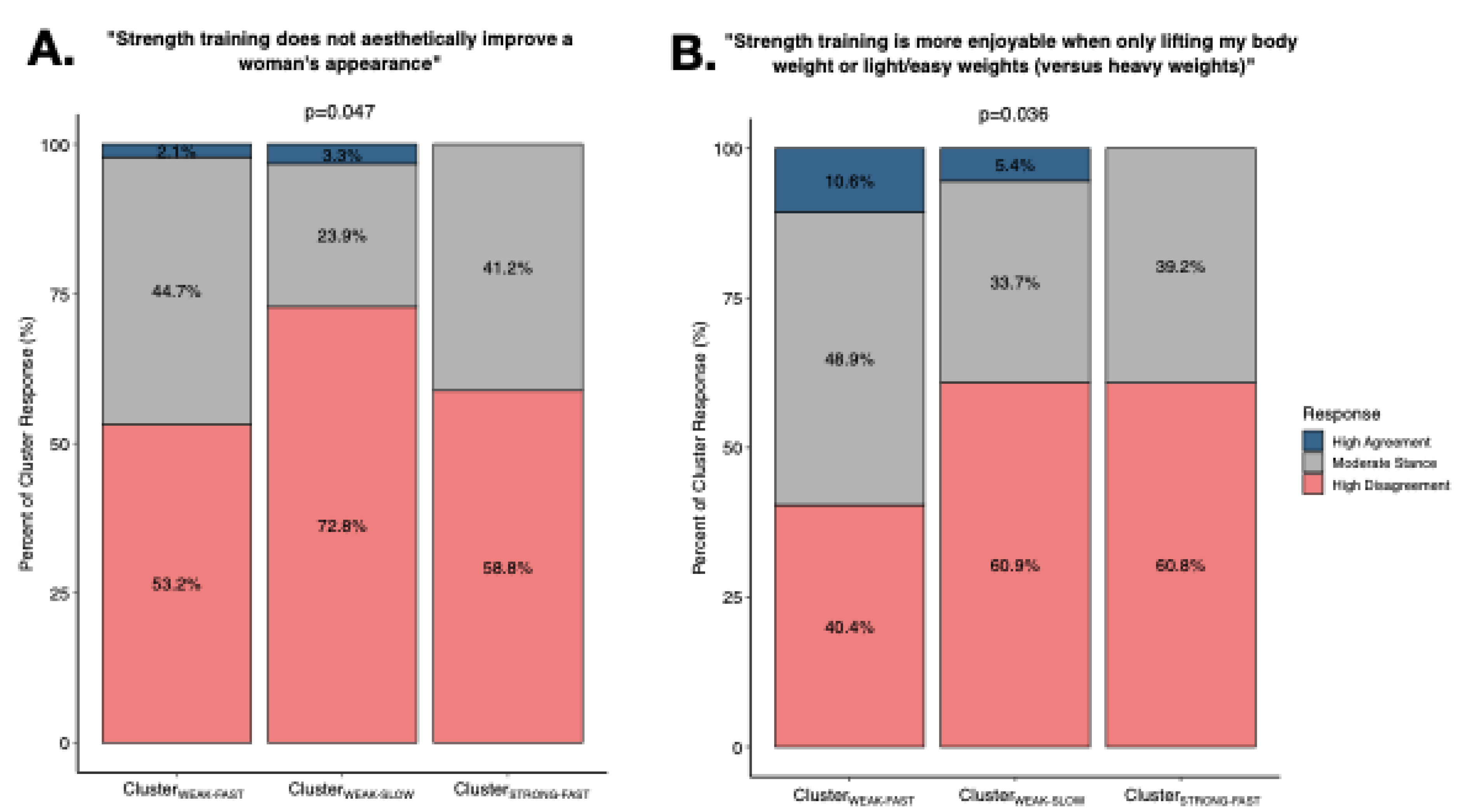


Figure 2: Athlete Neuromuscular Strength Profile is Associated with Attitudes Towards Strength Training.

DISCUSSION

- Three clusters representing distinct neuromuscular strength profiles were identified in female university athletes.
- Profile 3 demonstrated greater maximal muscle strength, leg power, plyometric capacities and faster CMJ contraction times relative to the other two profiles.
- There were subtle but significant differences in attitudes towards strength training between profiles.
- Observationally, we noted that profiles 1 and 2 (characterized by lower maximal muscle strength, leg power output, and slower CMJ contraction times) experienced most of the ACL injuries in the sport season following baseline testing.

CONCLUSIONS

- Unsupervised machine learning may provide advantages over traditional methods to examine neuromuscular strength baseline testing.
- Although a link between neuromuscular strength and attitudes towards training was observed, this relationship warrants further exploration

PRACTICAL APPLICATIONS

- Establishing data-driven neuromuscular strength profiles is critical for determining strength thresholds that can be used to guide strength training and rehabilitation in athletes.
- In doing so, coaches can move away from a *more is better* approach and can train strength capacities specific to an athlete's athletic demands.
- This approach can be combined with other analyses to help characterize when ACL-injured athletes have sufficiently rehabilitated and display a set of neuromuscular strength characteristics indicative of *performance-readiness*.

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