Part 4.2 Research Synthesis & Recommendations Report

Introduction

Force-plate testing has become very important in collegiate sports performance monitoring, but most published research relies on single-sport cohorts, elite male samples, or short laboratory-based trials rather than multi-team, real-world datasets. This creates a gap in understanding how neuromuscular performance patterns range across different collegiate sports and how athletes differ in their responses to training and fatigue. To address this gap, our project focused on five metrics: system weight, peak velocity, jump height, peak propulsive force, and average propulsive force. We selected these metrics because they are strongly supported within sports and science literature and are consistently represented in our university's dataset. Research shows that peak velocity reflects neuromuscular efficiency and training readiness, jump height is one of the most reliable indicators of explosive performance and fatigue (Taylor et al., 2021; Alba-Jiménez et al., 2022), and propulsive force metrics are directly linked to jump mechanics and acceleration capacity (Bobbert et al., 1992; Reiser et al., 2000). System weight is also essential because force outputs must be interpreted in relation to total mass to make insightful comparisons (Keesey, 1993; Wilmore & Costill, 1994). These literature gaps and practical considerations helped us create our research question: How do these five metrics vary across athletes from multiple collegiate sports, and how do these values relate to known normative ranges? This analysis aims to bridge the gap between controlled laboratory research and practical, real-world athlete monitoring by utilizing a large, integrated dataset.

Methods

We analyzed force-plate records from the research_experiment_refactor_test table. The five selected metrics were chosen because of their representation in the data and widespread use in readiness monitoring. Peak velocity is known to respond sensitively to load manipulation and reflects overall explosiveness (Cormie et al., 2012), while jump height provides a consistent indicator of fatigue and stretch-shortening cycle function (Taylor et al., 2021). Propulsive force metrics are directly linked to jump performance and mechanical power (Bobbert et al., 1992; Sensors, 2023), making them appropriate for comparison. Data cleaning procedures included converting timestamps, translating metric values to numeric form, filtering data to a 12-month window for individual athlete analysis, and extracting records for two athletes (PLAYER_1239 and PLAYER_691) and two teams (Stony Brook Men's Soccer and Men's Basketball). Statistical analyses included simple linear regression to evaluate performance trends over time and independent samples t-tests to compare jump height between teams. Visualization outputs included line plots for individual athletes, boxplots for team comparisons, and monthly testing frequency charts to examine data collection patterns. These steps provided a structured approach for identifying both individual athlete and team differences.

Results

The individual athlete analyses displayed two differing neuromuscular profiles. PLAYER_1239 displayed stable or improving trends across all five metrics during the past 12 months. Peak velocity, jump height, peak force, and impulse all showed small but positive slopes, and the athlete's best performances occurred in late 2024. These patterns coordinate with existing literature demonstrating that consistent training loads and adequate recovery support positive trends in velocity and jump metrics (Cormie et al., 2012; Taylor et al., 2021). System weight was constant throughout the monitoring period, confirming that improvements were not due to changes in body mass but due to genuine neuromuscular adaptation. In contrast, PLAYER_691 showed significant declines in peak velocity, jump height, peak propulsive force, and impulse. The sharp downturn beginning around June–July 2024 suggests accumulated fatigue or disruptions in training continuity, which matches research that identifies reductions in jump height and propulsive force as early indicators of neuromuscular fatigue (Alba-Jiménez et al., 2022; Reiser et al., 2000). Although system weight fluctuated a little, the changes were not significant enough to explain the performance decline, reinforcing the interpretation that neuromuscular readiness had worsened.

Team-level comparisons reflected sport-specific demands stated in the literature. Men's Basketball athletes displayed higher jump height values and more frequent force-plate testing, which aligns with the sport's reliance on repeated explosive jumps and rapid directional movements. Men's Soccer, on the other hand, displayed lower jump heights and more inconsistent testing patterns, which corresponds with soccer relying on aerobic capacity, sprinting, and high-speed running rather than continuous vertical power outputs. These findings align with published normative ranges indicating that basketball athletes typically achieve higher jump heights than soccer athletes due to different movement profiles and training habits (Topend Sports, n.d.). The t-test revealed significant differences between the two teams, suggesting that sport-specific neuromuscular profiles are clearly detectable using force-plate metrics. Analyzing frequency also revealed long periods without testing between 2019 and 2021, followed by a sudden surge in 2022 and inconsistent patterns afterward. These irregularities suggest shifts in equipment usage, staffing, or monitoring workflows rather than changes in athletic performance.

Discussion

The findings reinforce and enhance conclusions found in current sports-science literature. PLAYER_1239's positive trends support research indicating that peak velocity and jump height improve when athletes go through well-structured training cycles (Cormie et al., 2012; Taylor et al., 2021). Meanwhile, PLAYER_691's declines are consistent with research showing that neuromuscular fatigue reduces explosive performance, especially in propulsive force and jump height (Alba-Jiménez et al., 2022; Reiser et al., 2000). These patterns verify the reliability of the selected metrics as readiness indicators and demonstrate how force-plate data is able to capture each athlete's individual adaptation process.

At the team level, the differences between soccer and basketball support known sport-specific kinetic profiles and confirm normative expectations reported in the literature. Basketball athletes naturally produce higher jump outputs due to more frequent explosive actions, whereas soccer athletes typically have lower normative ranges since their performance relies more on sprint velocity and endurance (Haugen, et al., 2022; Topend Sports, n.d.). However, testing frequency across teams and seasons was uneven, with elongated gaps and inconsistent monitoring likely caused by factors such as staffing availability, scheduling constraints, device access, and differing adherence to testing protocols. While the team differences and overall metric patterns align with published norms, this irregular data collection limits the accuracy of short-term trend interpretation and cross-season comparisons.

Our analysis addresses several key gaps identified in the literature review. Most research focuses on single sports or controlled laboratory environments, while our dataset offers long-term, real-world, multi-team data. This allowed us to examine cross-sport differences, multi-month readiness trends, and performance variance across seasons, which are all areas where research is limited. Practical implications include the opportunity to implement an automated flag system to identify performance changes. For example, PLAYER_691's significant decline in multiple metrics would likely trigger a flag, telling coaches to adjust training load or recovery plans. Consistent and standardized data collection would strengthen the usefulness of these systems by improving early detection of meaningful performance changes. It was surprising that PLAYER_691's performance decline was so sharp and consistent across all metrics, and that testing frequency across years fluctuated so heavily. However, the team differences and overall metric patterns matched published norms, which increases confidence in the dataset's accuracy.

Limitations and Future Directions

Although the dataset contains countless rows, many limitations affect interpretation. Testing frequency was inconsistent, especially before 2022, which introduces uncertainty about seasonal trends. This uneven data collection is most likely due to operational constraints such as staffing limitations, scheduling conflicts, inconsistent team compliance, and limited access to force-plate equipment, rather than true changes in athlete performance. The dataset also lacks contextual information such as training load, injuries, fatigue scores, or wellness indicators, all of which are important for interpreting changes in force-plate performance. Team labels were sometimes inconsistent, requiring manual recoding, and the dataset only includes vertical-jump metrics without complementary GPS or sprint data.

Future research would benefit from integrating force-plate, GPS, and wellness information to create more comprehensive athlete profiles. Implementing standardized testing schedules and clearer testing protocols across teams would help reduce data irregularity in future seasons. Longitudinal predictive modeling could also be developed to identify early warning signs of fatigue or injury risk. Implementing an automated flagging system could help coaches quickly identify underperforming athletes and pinpoint overperformers whose training habits may offer useful insights. More consistent data collection across seasons would substantially improve the reliability and interpretability of longitudinal trend analyses.

References

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