Exacting Trends and Selecting Kit within Elite Male and Female Track Cyclists in the Team Sprint Event

Introduction

This case study, conducted in partnership with Team GB Track Cycling, is a retrospective analysis of training and competition data aimed at identifying determinates of success and underlying themes across the different positions of the team sprint. The team sprint consists of two teams, each with three positions: position one (P1), position two (P2), and position three (P3). All three positions start simultaneously, with the lead athlete (P1) peeling off after the 1st lap, followed by P2 after the second lap, and with P3 finishing the race after the 3rd lap. The team with the fastest time, proceeds to the next round, typically there are three rounds in total. With each lap being 250m long, a team that completes all three rounds will have completed 750m-2250m depending on the position.

Previous research analysing the team sprint has shown peak torque normalized to system mass is a significant determinant of 15m, 65m, and 125m performance (Kordi & Van Rijswijk, 2024). However, a primary limitation of this work was its focus on the first lap, leaving any relationships with the 2nd and 3rd lap(s) under researched. Moreover, participants' position within the team sprint was not specified. Considering the varying demands of each position, metrics such as peak torque and power are likely to change based on position specific gear ratio and event duration. Other research has established the relationship between torque, power and 200m performance but has not analysed longer sprint distances, which are highly relevant in the team sprint (Dorel et al., 2005).

The relationship between average cadence and overall time has been previously identified, recognizing that as mean pedal force decreases, cadence increases (Dunst &

Grüneberger, 2021). This may suggest a potentially optimal cadence, situated along the parabolic arc. Since cadence is largely a function of gear ratio, understanding this relationship may help in selection of the optimal gear ratio (Faria et al., 2005). Supporting this theory, torque-power-velocity profiles have been used to determine optimal cadence (Imbery et al., 2022). While this work provides insight into the torque-power-velocity relationship of cycling, there are key factors that limit applicability, such as the use of variable gearing which is not available in track cycling.

In summary, exploring the influence of torque, power, cadence, and equipment changes such as gearing and wheel type on overall time for each position within the Team GB Track Cycling squad may be beneficial to team sprint performance. Additionally, exploring correlations between split distances and overall time may prove useful for informing targeted training strategies.

Methods

Data Collection

Data were collected by Team GB Track cycling from June 2022 to April 2025. The dataset consists of 3797 bouts from 19 athletes (10 men, 9 women). Seven types of efforts were recorded (standing 60m, 125m, 250m, 375m, 500m, 750m, and 1000m) with times recorded at each multiple distances (ex. 0-10m. 0-60m, 0-250m, 60-125m, half laps, and laps). Gear configuration was recorded for each bout, including bike, helmet, suit, gear, and wheel type. Data was originally recorded in a long format and lacked a session ID. Session IDs were added based on unique and repeating variables before pivoting the data to a wide format for statistical analysis.

Statistical Analysis

All analysis were performed in Python (version 3.13.2) using the Pandas, Numpy, and StatsModels libraries. Data entries with values beyond 3 standard deviations of the group mean were removed from the dataset, as they were likely an error.

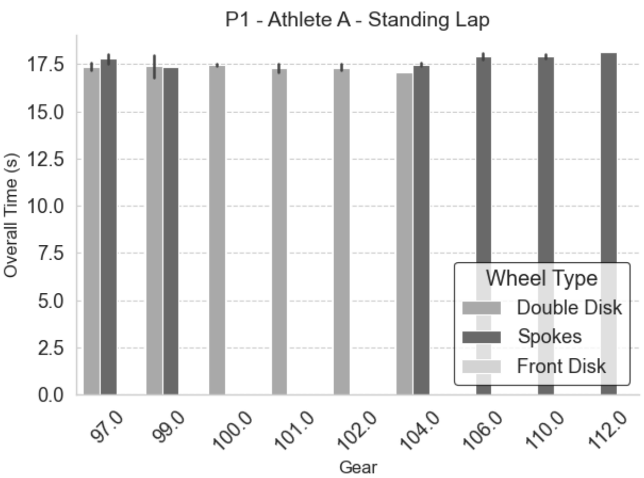
First, a descriptive analysis was conducted to assess performance differences based on kit configuration. For each athlete, effort type was selected based on the distance they would compete in for the team sprint: P1 at 250m, P2 at 500m, and P3 at 750m. Descriptive statistics were calculated for different gear and wheel combinations to identify potentially optimal configurations. This analysis of kit selection was observational in nature and does not generate statistical predictions or inferential outcomes. Athletes who only used one wheel type and one gear type were removed from this analysis due to the lack of within-athlete comparisons.

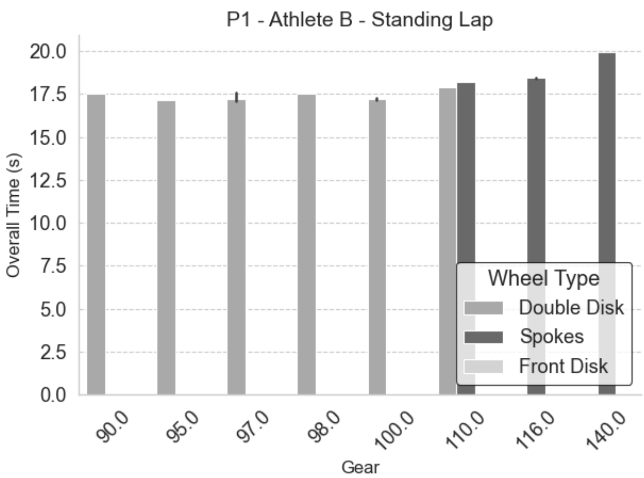
Second, to identify trends and correlations in the different positions, regression modelling was used on performance metrics with overall time as the dependant variable. Previous research has shown that quadratic regression modelling has been effective in correlating power-velocity relationships in cycling (Dorel et al., 2005). For that reason, each independent variable will use linear, quadratic, or logarithmic models. Best fit will then be determined via a combination of p-value and Akaike Information Criterion (AIC), with a lower p-value being better, and with the lowest AIC score being the best fit (Darnius et al., 2019; Eric W. Klee, 2008). Linear fit models with similar p-values, AIC scores, and coefficient of determination (R^2) values were prioritized as they are simpler and provided similar amounts of information to the quadratic and logarithmic calculations. When linear models were determined unsuitable, R^2 and AIC were used to determine the best alternative fit.

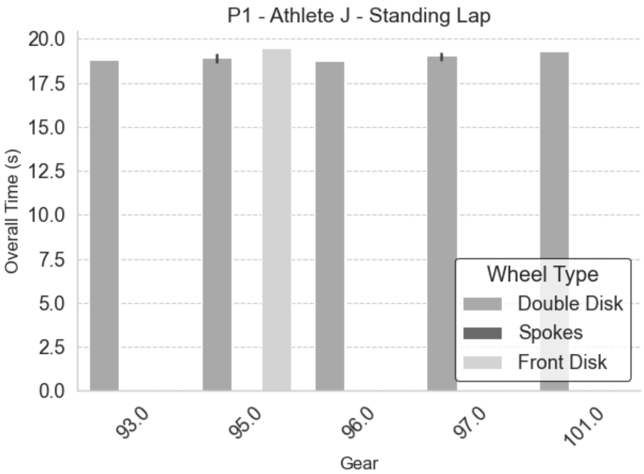
Results

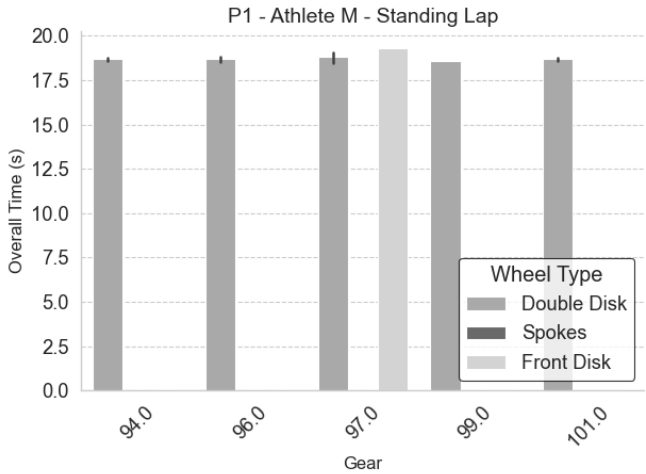
Kit Configuration

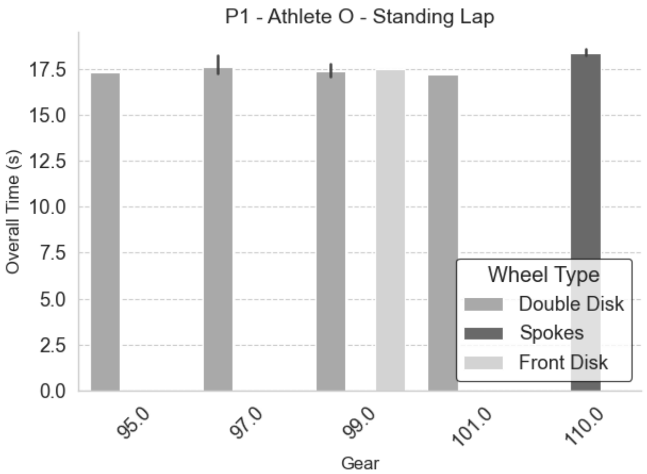
Gear and wheel combinations were calculated for a total of 12 athletes. Three athletes participated in more than one position, their data were separated and calculated for both positions. Athletes with insufficient sample size for each configuration (e.g. only 1 sample per gear or wheel type) were excluded from this analysis due to the inability to draw meaningful conclusions. All participants performed better in their respective events with the double disk wheelset. Direct comparisons between wheelsets were limited by inconsistent pairing with gear ratios, meaning observed differences may be confounded by gear configuration. The mean of the fastest gear for position 1, 2, and 3 was 99.0±3.67, 112.7±2.08, 114.0±1.73, respectively. The differences in typical gearing were expected as a slower acceleration speed, due to a higher gear ratio, is less detrimental over a longer distance.

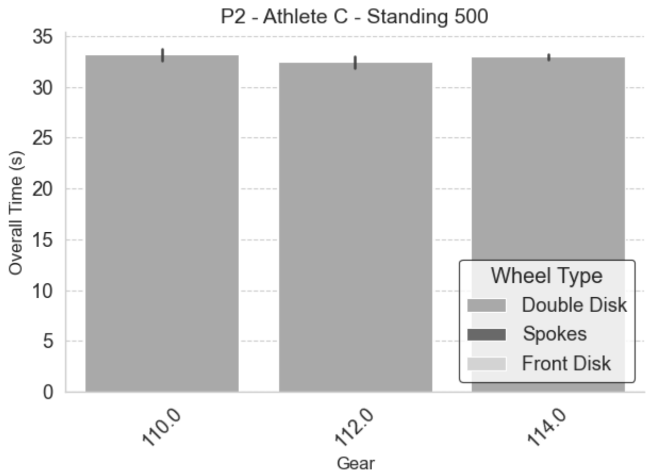


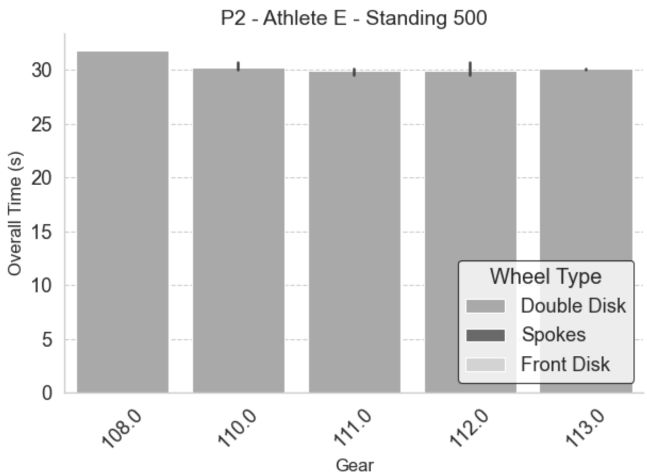


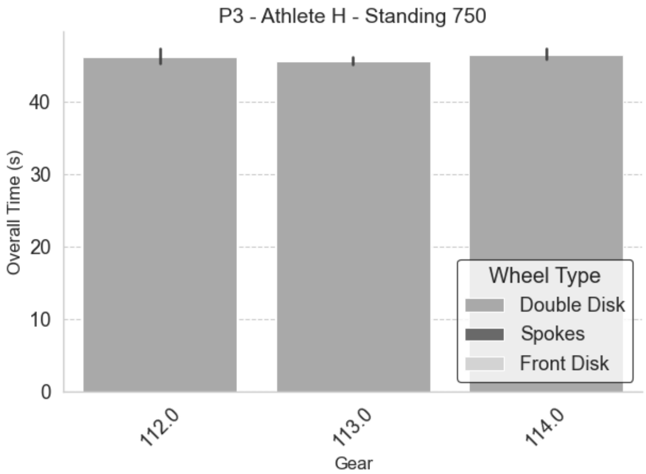

P1 - Athlete J - Standing Lap
Overall Time (s)
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5
20.0
Gear
93.0
95.0
96.0
97.0
101.0
Wheel Type
Double Disk
Spokes
Front Disk

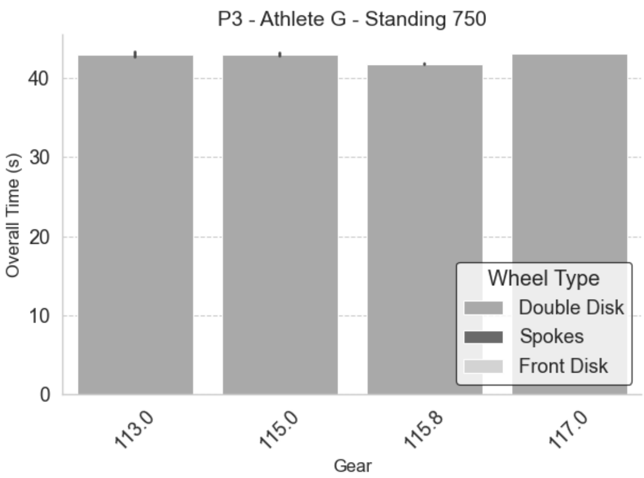

P1 - Athlete M - Standing Lap
Overall Time (s)
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5
20.0
Gear
94.0
96.0
97.0
99.0
101.0
Wheel Type
Double Disk
Spokes
Front Disk

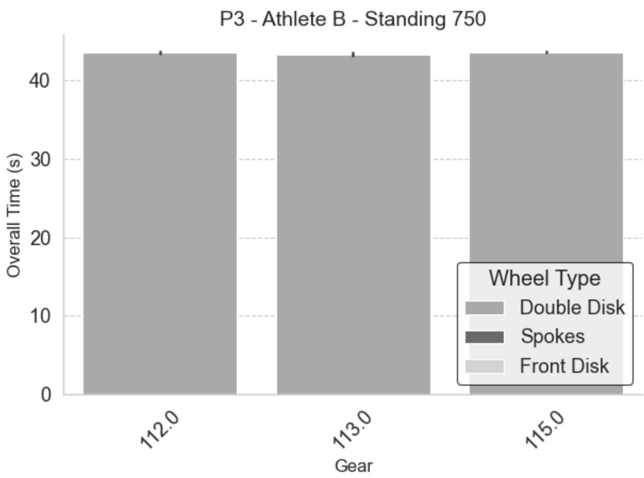

P1 - Athlete O - Standing Lap
Overall Time (s)
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5
Gear
95.0
97.0
99.0
101.0
110.0
Wheel Type
Double Disk
Spokes
Front Disk


P2 - Athlete C - Standing 500
Overall Time (s)
0
5
10
15
20
25
30
35
Gear
110.0
112.0
114.0
Wheel Type
Double Disk
Spokes
Front Disk


P2 - Athlete E - Standing 500
Overall Time (s)
0
5
10
15
20
25
30
Gear
108.0
110.0
111.0
112.0
113.0
Wheel Type
Double Disk
Spokes
Front Disk

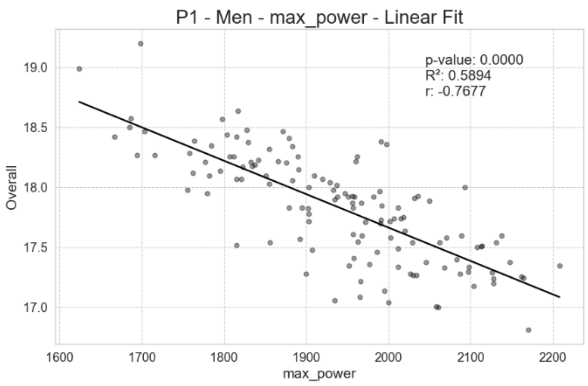

P3 - Athlete H - Standing 750
Overall Time (s)
0
10
20
30
40
Gear
112.0
113.0
114.0
Wheel Type
Double Disk
Spokes
Front Disk

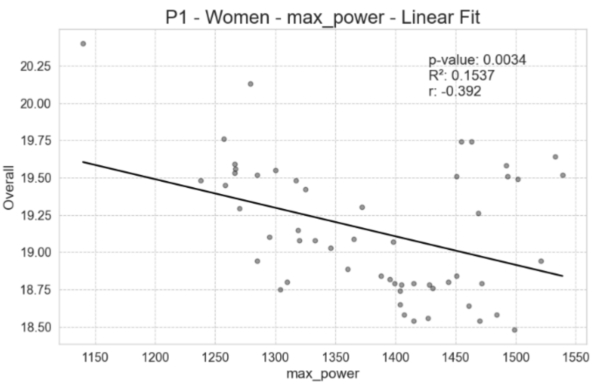


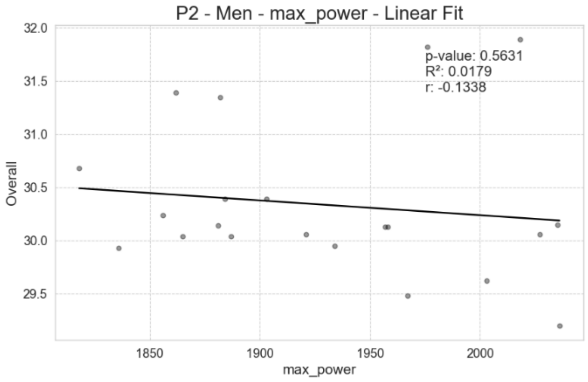


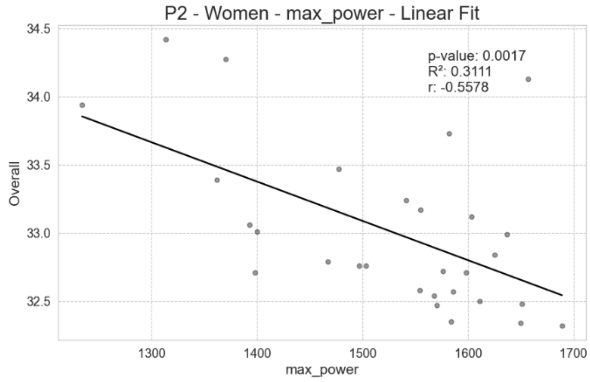
Peak Power

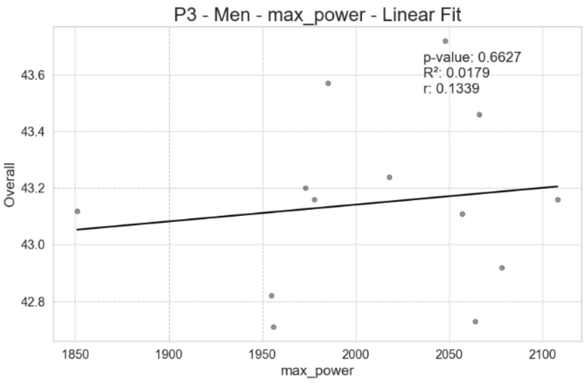
The correlation between peak power and overall time for P1 was significant in men's (p = 0.00, r = -0.7677, n = 132) and women's groups (p = 0.0034, r = -0.393, n = 54). The women's group for P2 showed statistical significance (p = 0.0017 and r = -0.5578, n = 29) while the men's group did not (p = 0.5631, r = -0.01338, n = 21). In P3, both men's and women's groups showed non-significant values (men: p = 0.6627, r = 0.1339, n =13, women: p = 0.6311, r = 0.1178, n = 19).

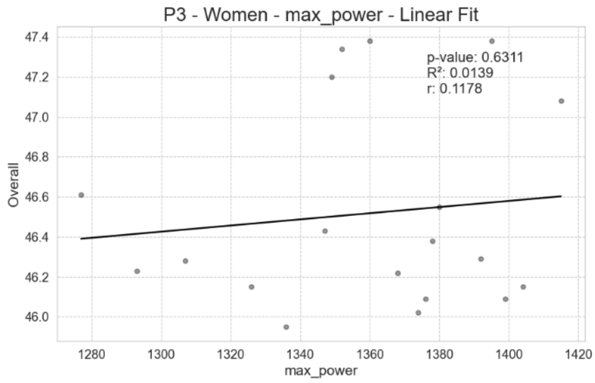






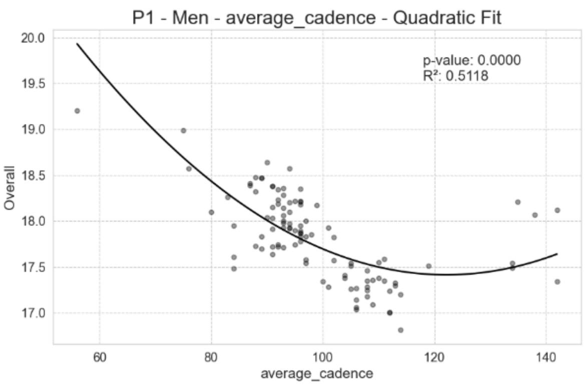


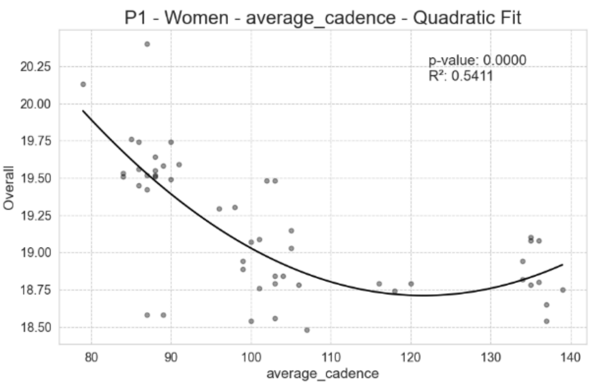


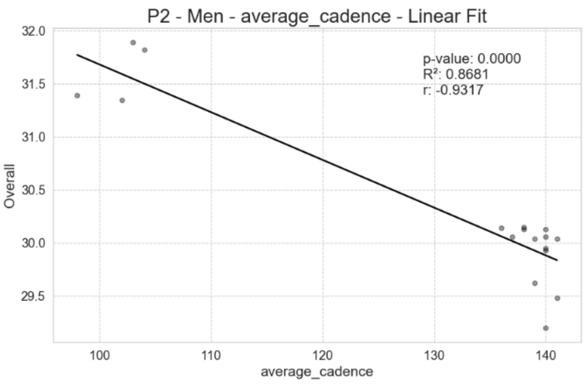


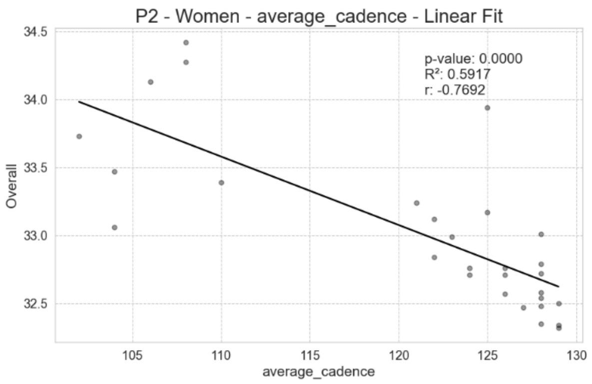
Average Cadence

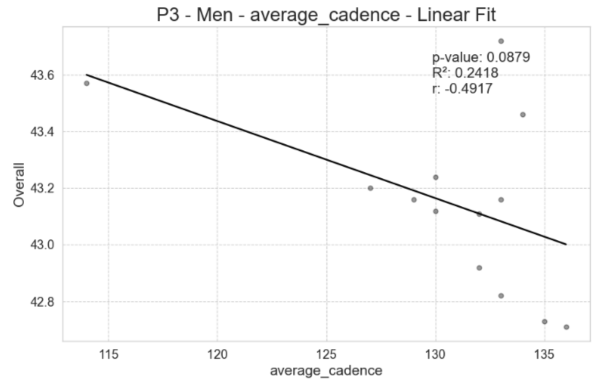
Correlation between average cadence and overall time in P1 showed significance and moderate R^2 values (men: p = 0.00, R^2 = 0.5118, n = 103; women: p = 0.00, R^2 = 0.5411, n =51). In P2, significance was also determined with strong and moderate r values (men: p = 0.00, r = -0.9317, n= 17; women: p = 0.00, r = -0.7692, n = 29). The women's group in P3 had significance (p = 0.00, r = -0.8483, n = 19) whereas the men's group did not (p = 0.0879, r = -0.4917, n = 13).

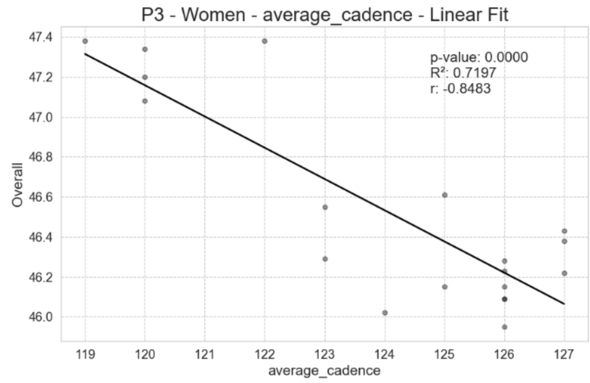






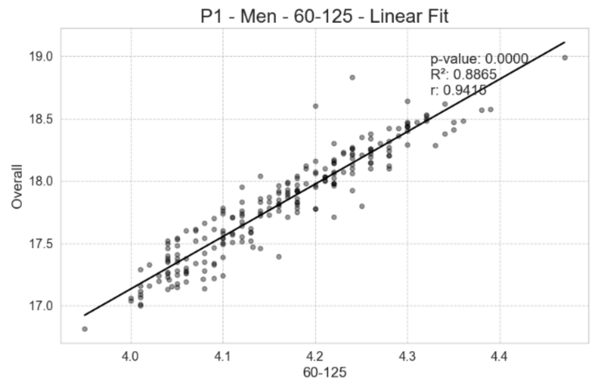


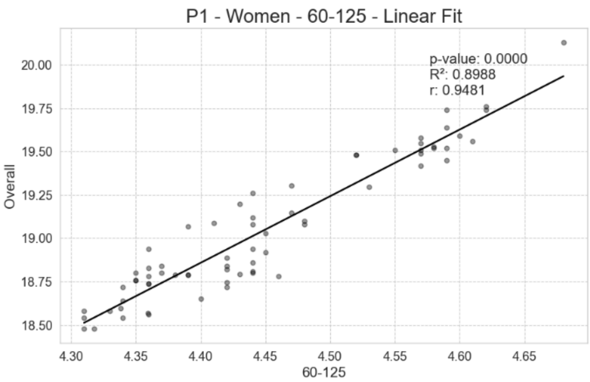


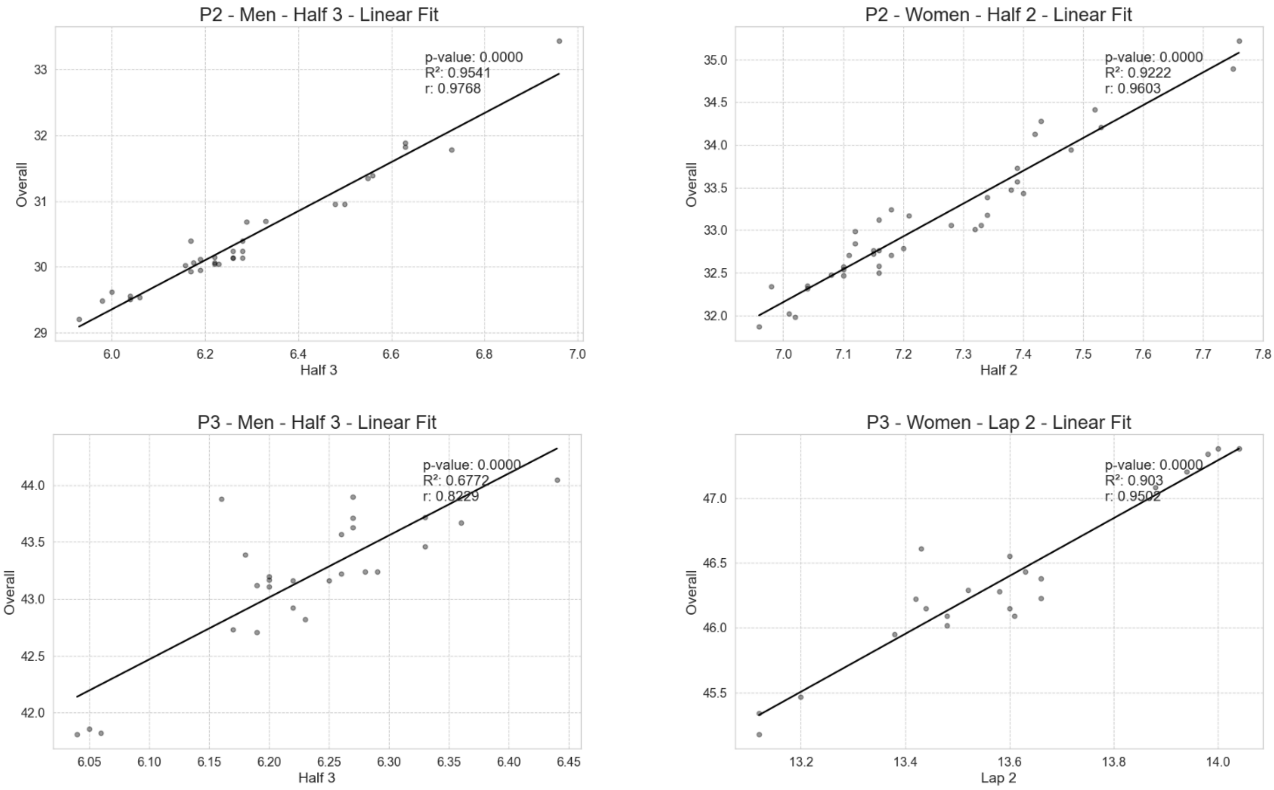


Split Times

The correlation of timed splits to the overall time were calculated for each of the 6 groups. Men's and women's P1 were most strongly correlated with 60-125m (men: $p = 0.00$, $r = 0.9415$, $n = 221$; women: $p = 0.00$, $r = 0.9481$, $n = 68$). The overall time in men's P2 was best represented by "Half 3" (1st half of the 2nd lap) ($p = 0.00$, $r = 0.9768$, $n = 32$). In the women's group, "Half 2" (2nd half of the 1st lap) was the most strongly correlated split ($p = 0.00$, $r = 0.9603$, $n = 39$). Men's P3 was best represented by "Half 3" (1st half of the 2nd lap) ($p = 0.00$, $r = 0.8229$, $n = 26$) and women's P3 showed the strongest correlation with Lap 2 ($p = 0.00$, $r = 0.9502$, $n = 22$).







Discussion

Gear ratios and wheel combinations appeared to influence overall performance time all positions of the team sprint. All athletes performed better with the double disk wheelset, despite initial assumptions that increased rolling resistance would limit its effectiveness over shorter distances, specifically in P1 (Burke, 2003; Faria et al., 2005). Due to inconsistent gear-wheel pairings and small sample sizes (n < 5 per configuration), formal hypothesis testing via a paired t-test was not feasible. While trends were visible in descriptive statistics, it should also be noted that there may be other motives (e.g. training or coaching strategies) that could limit the validity of any performance conclusions.

Peak power showed its strongest correlation with overall time in the P1 men's group (r = -0.7677), aligning with previous findings that highlight its role in short-distance sprinting (Dorel et al., 2005). This influence diminished as duration increased, particularly in men. This decline likely reflects the increasing contribution of endurance, pacing, and need for a fast start over extended sprint durations. Notably, the women's P2 group showed stronger correlations than expected, possibly due to higher-variance performances or different pacing strategies that were targeted through training. A key limitation in this analysis was the time at which peak power was achieved, as it was not reported. Knowing when an athlete achieves peak power could aid in a better understanding of how different event durations are influenced by this metric and/or the induced fatigue that may impair later splits.

Average cadence had a significant correlation with overall time in all positions, especially in P1. The quadratic relationship observed in both men's and women's P1 groups suggests that there is diminishing returns in performance at excessively high cadences. This parabolic trend is consistent with other research in athlete-specific cadence zones linked to torque-velocity-power models (Imbery et al., 2022). A low cadence may indicate that an athlete is unable to take full advantage of reaching their peak cadence; a high cadence may indicate that an athlete reaches their peak cadence too soon in the race and is sacrificing the potentially higher top speed of an increased gear ratio. These findings support the need for individualized cadence profiling and gear selection based on force-velocity characteristics.

In the other 2 positions, linear models were appropriate as there were minimal differences between differently fit models. This may be due to a reduction in sample size compared to P1 groups. If the sample size(s) were larger and had enough variance of gear ratios, we may also see a parabolic trend in overall performance. Given that cadence is influenced by gear ratio, these findings may help inform kit selection. Athletes unable to exploit their optimal cadence range may be compromising their performance due to sub-optimal gear ratios. Additional profiling of cadence and gear ratio may aid in the understanding of this relationship and enable the selection of optimal gearing for specific distances.

Across all positions, split times showed varying degrees of correlation with overall time. 60-125m performance emerged as the strongest correlate to the men's and women's P1 groups, likely due to its proximity to the acceleration phase. This segment also reflects the momentum from the initial 0-60m, suggesting a compounding metric for start efficiency. A 0-125m split, which was not included in the dataset, may offer a more holistic view of start performance and therefor serve as a more practical benchmark. In men's P2, the strongest correlation was with "Half 3" (1st half of the 2nd lap), whereas the women's was with "Half 2" (2nd half of the 1st lap). Notably, both groups showed very high correlation with "Half 2", "Half 3", "Half 4", lap 1, and lap 2 ($r >= 0.9$). While these metrics were statistically strong, their practical application in training is limited as they occur near the end of the effort. Interestingly, 60-125m remained reasonably strong (men: $r = 0.8543$; women: $r = 0.8568$). As observed in P1, the 60-125m split may serve as more practical benchmark for training due to its high correlation and relevance to early acceleration. Additionally, "Half 2" (2nd half of the 1st lap) demonstrated a very strong correlation in the men's group ($r = 0.9658$), suggesting it may be a more suitable training benchmark for both men and women by capturing the acceleration phase into the second lap.

In P3, the men's group had the highest correlation with "Half 4" (2nd half of lap 2) and the women's with lap 2. Like P2, longer splits typically yielded stronger correlations with overall time, likely due to cumulative pacing effects and reduced start variability. The men's group had high correlation with "Half 3", "Half 4", "Half 5", "Half 6", lap 2, and lap 3 ($p = 0$, $r = 0.8229$-0.8746). The women's group also showed high correlation in these same split distances ($p = 0$, $r = 0.8813$–0.9502). In the shorter distanced splits, the men's and women's groups had a moderate correlation with "Half 2" (men: $p = 0.00$, $r = 0.6576$; women: $p = 0.00$, $r = 0.6639$). As for the 60-125m split, both men and women had weak-moderate correlations (men: $p = 0.0137$, $r = 0.4773$; women: $p = 0.0226$, $r = 0.4837$). "Half 4" (2nd half of 2nd lap) may serve as the most practical benchmark for both groups, as it shows a strong correlation with performance (men: $p = 0.00$, $r = 0.8746$; women: $p = 0.00$, $r = 0.931$) and reflects the athlete's ability to accelerate into the final lap. Overall, different time splits in events can be useful training tools when trying to simulate a submaximal training set aimed at benchmarking race readiness.

Limitations

The statistics within this case study largely looked at group trends across the different positions of the team sprint. Because of this broader statistical analysis, relevance to individual athletes is reduced. Several high-influence athletes disproportionately contributed to certain datasets (e.g. P1 average cadence: athlete A contributed 32/61 trials), possibly skewing group-level trends. Participant bias may explain why average cadence shows a stronger quadratic fit, in contrast to the linear relationships in the other positions. Future research should aim to standardize kit setups across the participant population and investigate time-based power data to unpack the fatigue-performance relationship in efforts of optimizing gear selection for individual athletes. Despite these limitations, the findings still have applied relevance for high performance track cycling. Additionally, the data used in this case study largely consisted of training data which, while similar, may have a larger variance due to training modalities. In regards to using non-linear fit models for regression calculations, the interpretation of the coefficient of determination (R^2) does not necessarily indicate that a useful prediction can be made as it accounts for the prediction interval (Kutner, 2005). More simply, a high R^2 will explain the trend but is not necessarily very precise in pinpointing the prediction.

Conclusion

This case study highlighted several key factors influencing the team sprint performance in elite track cycling. All athletes performed better with the double disk wheelset, suggesting that its benefits outweigh its higher rolling resistance, even in shorter efforts. Peak power has a strong correlation to overall time, particularly in men, but loses significance in longer efforts. This reinforces the need to consider duration-specific power demands. Average cadence emerged as a strong correlate in all positions of the team sprint. Further investigation using non-linear fit models, such as the case with average cadence, may prove to be a viable method of determining optimal gear selection for each athlete. Understanding the correlational strength between split distances, especially those that represent the result of a good acceleration phase, provide practical benchmark data for training.

References

Burke, E. (2003). *High-tech Cycling*. Human Kinetics.

Darnius, O., Normalina, & Manurung, A. (2019). Model selection in regression linear: A simulation based on akaike's information criterion. *Journal of Physics: Conference Series*, *1321*(2), 022085. https://doi.org/10.1088/1742-6596/1321/2/022085

Dorel, S., Hautier, C. A., Rambaud, O., Rouffet, D., Praagh, E. V., Lacour, J.-R., & Bourdin, M. (2005). Torque and Power-Velocity Relationships in Cycling: Relevance to Track Sprint Performance in World-Class Cyclists. *International Journal of Sports Medicine*, *26*(9), 739–746. https://doi.org/10.1055/s-2004-830493

Dunst, A. K., & Grüneberger, R. (2021). A Novel Approach of Modelling and Predicting Track Cycling Sprint Performance. *Applied Sciences*, *11*(24), Article 24. https://doi.org/10.3390/app112412098

Eric W. Klee. (2008). *Akaike Information Criterion—An overview*. Science Direct. https://www.sciencedirect.com/topics/medicine-and-dentistry/akaike-information-criterion

Faria, E. W., Parker, D. L., & Faria, I. E. (2005). The Science of Cycling. *Sports Medicine*, *35*(4), 313–337. https://doi.org/10.2165/00007256-200535040-00003

Imbery, F., Leo, P., Wakefield, J. J., & Schoberer, U. (2022). Torque behaviour during cycling sprints from different pedalling frequencies. *Journal of Science and Cycling*, *11*(2), Article 2. https://www.jsc-journal.com/index.php/JSC/article/view/748

Kordi, M., & Van Rijswijk, I. (2024). Performance analysis and mechanical determinants of the opening lap of the team sprint in elite-level track cycling. *European Journal of Sport Science*, *24*(9), 1240–1246. https://doi.org/10.1002/ejsc.12158

Kutner, M. H. (Ed.). (2005). *Applied linear statistical models* (5th ed). McGraw-Hill Irwin.