applied sciences

MDPI

Article

Relationship Between Half Squat Load–Velocity Profile and Cycling Power Profile in Masters-Level Cyclists

Fran Oficial-Casado [1,*], Alexis Soriano-Gandia [2] and Jose Ignacio Priego-Quesada [1]

[1] Research Group in Sport Biomechanics (GIBD), Department of Physical Education and Sports, Universitat de València, 46010 Valencia, Spain; j.ignacio.priego@uv.es
[2] Movistar Pro-Cycling Team, 31486 Egües, Spain; alexisgandiasoriano@gmail.com
* Correspondence: francisco.oficial@uv.es

Featured Application

The findings of this study suggest that load–velocity profiling derived from conventional strength exercises, such as the half squat, may have limited applicability for assessing cycling performance in masters-level cyclists. Practitioners may benefit from prioritizing cycling-specific assessments, such as power-duration profiling, when evaluating performance and guiding training interventions.

Abstract

Background: Cycling performance depends on both aerobic capacity and neuromuscular function, with recent training approaches emphasizing the role of strength training. However, the extent to which neuromuscular characteristics assessed in conventional strength exercises transfer to cycling performance remains unclear. Therefore, the aim of this study was to analyze the relationship between the Load–Velocity (L-V) profile obtained from a multi-joint strength exercise (half squat) and the cycling Power Profile (PP) in Masters-level cyclists. **Methods**: Twelve masters-level cyclists were evaluated by the L-V and the PP test. The cycling PP was determined through maximal efforts of 1, 5, and 20 min, expressed relative to body mass ($W \cdot kg^{-1}$). The L-V profile was assessed during the half squat using a progressive loading protocol with load–velocity monitoring. Pearson's correlation analyses were performed between the slope and intercept of the L-V profile relationship and PP variables, as well as mean ascent velocity (VAM). **Results**: No significant relationships were observed between L-V profile variables and cycling performance (r = −0.21 to 0.09, $p > 0.05$). In contrast, VAM showed very large associations with P1 (r = 0.81, $p = 0.001$) and P5 (r = 0.86, $p < 0.001$). The regression model explained a large proportion of the variance in VAM ($R^2 = 0.75$, $p = 0.01$). **Conclusions**: Strength performance assessed through a conventional exercise such as the half squat is not directly related to cycling PP in masters-level cyclists. The observed relationships between VAM and cycling PP reinforce the importance of task specificity.

Keywords: cycling performance analysis; strength training; velocity-based training; cycling ascent performance; performance test

Academic Editor: Alfonso Penichet-Tomás

Received: 22 April 2026
Revised: 19 May 2026
Accepted: 22 May 2026
Published: 26 May 2026

1. Introduction

Cycling performance is primarily determined by the ability to generate mechanical power through the effective application of pedal forces, the index of mechanical effectiveness, and cadence [1]. These mechanical determinants are closely linked to the neuromuscular function of the main muscles involved in pedaling [2]. Consequently, neuromuscular performance plays a critical role in shaping the cycling Power Profile (PP), influencing performance across a wide spectrum of efforts ranging from maximal sprint power [3] to prolonged endurance performance [4]. Cycling PP has become a widely used test following the popularization of power meters, which enable an easy quantification of a cyclist's power output during training and competition [5]. Performance in the PP has been shown to correlate strongly with maximal mean power outputs recorded during competition [5,6] and endurance physiological variables [7]. Furthermore, the physiological and mechanical demands of cycling competitions are increasingly being quantified through power-based models that differentiate between race categories and formats [8]. Consequently, modern training methodologies aim to replicate these demands to optimize performance [9,10].

Although road cycling performance is largely dependent on aerobic metabolism [11,12], recent training approaches have increasingly incorporated concurrent strength and endurance training due to its potential to enhance performance beyond that achieved through endurance training alone [13]. Despite ongoing debate regarding the most effective strength training modalities for endurance cyclists, several approaches (including maximal strength training (4–10 RM), explosive training combined with high-resistance intervals, eccentric cycling, and single-leg cycling) have demonstrated additional performance benefits [4]. Strength monitoring training is essential to individualize training loads and in this sense, strength training assessment methods have evolved considerably over the last decade, largely due to advances in technology that allow precise monitoring of movement velocity, such as linear position transducers [14,15]. Velocity-based training has emerged as a practical and effective alternative to traditional percentage-based methods (e.g., %1 RM), particularly in contexts characterized by high training loads, such as road cycling [16]. Within this framework, the Load–Velocity (L-V) profile has been proposed as a valid tool to estimate relative load and to autoregulate training intensity based on movement velocity, enabling more individualized and adaptive training prescriptions [15,17]. Indeed, individualized L-V profiling may provide a more accurate representation of an athlete's neuromuscular status compared to group-based approaches, potentially leading to greater improvements in strength and power performance [14,17].

In cycling, recent methodological advances have enabled the assessment of L-V related characteristics during pedaling through torque-cadence profiling, demonstrating high reliability and strong relationships with performance indicators [18]. These approaches allow the evaluation of maximal dynamic force and the characterization of mechanical output across a wide range of cadences, providing valuable insights into cyclists' neuromuscular capabilities. However, relatively few studies have examined L-V profiling using conventional strength exercises such as the half squat [19–22]. The half squat is commonly implemented in cycling strength training [23–25] as it involves the main lower-limb muscle groups responsible for force production during pedaling [3] and allows standardized assessment of neuromuscular performance through L-V velocity [26]. While L-V relationships are well established in multi-joint strength exercises and widely used for training prescription [17,27], the extent to which these characteristics transfer to cycling-specific performance remains unclear. In this sense, to date, no studies have directly examined the relationship between the L-V profile obtained from a common multi-joint strength exercise, such as the half squat, and the PP in road cyclists. Addressing this gap may provide valuable insights into the transferability of neuromuscular qualities assessed in the gym to cycling-specific performance.

Therefore, the aim of this study was to analyze the relationship between the L-V profile obtained from the half squat and the cycling PP in masters-level cyclists. As a secondary objective, it was intended to examine whether the L-V profile in this population reflects sport-specific neuromuscular adaptations. It was hypothesized that, based on the existing evidence supporting the benefits of concurrent strength and endurance training, the cycling PP would be associated with the L-V profile, and that higher-performing cyclists would exhibit a more force-oriented profile.

2. Materials and Methods

2.1. Participants

Sample size estimation was performed using G*Power software (v.3.1.9.6; Universität Kiel, Kiel, Germany) [28]. Based on an expected large correlation (r = 0.70) between cycling power profile and load–velocity variables, with an alpha level of 0.05 and a statistical power of 80%, a minimum sample size of 11 participants was estimated for correlation analyses. Then, twelve male masters-level cyclists volunteered to participate in the study. Mean age was 43 $\pm$ 4 years (range: 37–50 years), body mass of 72 $\pm$ 5 kg, and height of 174 $\pm$ 5 cm. All participants had prior experience with both cycling performance testing and strength assessment protocols. They were experienced cyclists with 7 $\pm$ 2 years and their normal weekly training volume exceeded 200 km. Functional threshold power, derived from training and competition data recorded during the previous three months, averaged 3.7 $\pm$ 0.4 W$\cdot$kg^{-1}. All participants were familiarized with the half squat exercise, as it was regularly included in their strength training routines, which were performed with a frequency of 1–2 sessions per week. Participants were free from injury at the time of testing and provided written informed consent prior to participation. The study protocol was conducted in accordance with the Declaration of Helsinki and was approved by the Ethics Committee of Research in Humans of the Ethics Commission in Experimental Research of University of Valencia (ref. 2023-FIS-3176133).

2.2. Design

A cross-sectional study design was implemented to examine the relationships between cycling performance and strength-related variables. All testing procedures were conducted within two experimental sessions under standardized conditions. The cycling performance test was conducted on the first testing day, while the strength test was performed on the second testing day, with a one-week interval between sessions. Participants were instructed to avoid strenuous exercise in the 24 h prior to testing and to maintain their habitual diet and hydration status, as well as their usual sleep routine. Body mass assessment was conducted before each testing session using a digital scale (Tanita BC-601, Tanita Corp., Tokyo, Japan).

2.2.1. Cycling Performance Test

To assess cycling performance, a PP test was conducted [5]. Participants completed a standardized 30 min cycling warm-up at 40–60% of their estimated 20 min maximal mean power output (P20). Between minutes 10 and 20, four 30 s progressive efforts were performed, reaching approximately 110–120% of the estimated P20, with 2–3 min of active recovery between repetitions. The PP test consisted of maximal efforts of 1 min (P1), 5 min (P5), and 20 min (P20) performed on a constant uphill gradient of 6–8%. Adequate active recovery periods (>15 min) were conducted between trials. Cycling power output was measured using commercially available power meters (Garmin Vector, Olathe, KS, USA; SRM GmbH, Jülich, Germany and Quarq, SRAM LLC, Chicago, IL, USA), which have demonstrated acceptable validity and reliability across multiple device types and brands under a wide range of testing conditions [29].

2.2.2. Strength Test

Lower-body neuromuscular characteristics were assessed through an L-V profiling approach during a multi-joint resistance exercise (half squat), through a progressive loading test performed in a Smith machine [21,26,27]. The starting position was determined using a goniometer prior to testing, ensuring a knee flexion angle of 90º. An elastic band was positioned to standardize squat depth across all repetitions. Stance width and foot position were individualized and maintained across all repetitions. A standardized warm-up was performed, consisting of 5 min of lower-body joint mobilization followed by three sets of five squat repetitions with fixed loads of 20, 30 and 40 kg [29]. The initial load was set at a load between 50 and 60% kg of the participant's body mass and progressively increased in equal increments until mean propulsive velocity (MPV) reached, approximately, 80% of the estimated one-repetition maximum (1RM) [27]. Each participant completed a total of five sets. For each load, participants performed 3–5 repetitions, ensuring maximal intended velocity execution. Loads were applied in randomized order, and rest intervals between sets were set at 3 min to ensure adequate recovery between sets [21,30,31].

Bar velocity was recorded using a linear position transducer (Chronojump Boscosystem, Barcelona, Spain), with data sampled at high frequency and processed using manufacturer-specific software. MPV was calculated during the propulsive phase of the concentric action, defined as the portion of the movement where acceleration exceeded gravitational acceleration.

2.3. Data Processing

Data processing and further analyses were performed using RStudio software (v.2024.2.1; R Core Team, 2023). For cycling performance, P1, P5, and P20 were obtained for each participant and expressed relative to body mass ($W \cdot kg^{-1}$). Mean ascent velocity (VAM_{P20}) was calculated as the average vertical ascent speed per hour derived from the P20 test and expressed in $m \cdot h^{-1}$. A linear regression model was fitted to describe the power-duration relationship, from which the slope and intercept of the cycling PP were extracted. From the strength test, the best MPV of each load was selected to obtain the individualized L-V profile, and the following variables were derived: maximal theoretical velocity (v_0), maximal theoretical load (C_0), and the slope of the L-V relationship [32]. In addition, C_0 was expressed relative to body mass (1RM_rel) [21]. Potential outliers were identified using the interquartile range (IQR) method.

2.4. Statistical Analyses

Normal distribution of all variables was assessed using the Shapiro–Wilk test with a significance threshold set at $p < 0.05$. Descriptive statistics (means, standard deviations (SD), minimum and maximum values) were calculated to summarize all variables.

To evaluate the linear association between cycling and strength variables, Pearson's correlation coefficients (r) were calculated. Based on the absolute values of r ($|r|$), correlations were interpreted as trivial ($|r| < 0.1$), small (0.1–0.3), moderate (0.3–0.5), large (0.5–0.7), very large (0.7–0.9), or extremely large (>0.9) [33]. Additionally, a multiple linear regression model was constructed to examine the contribution of short-duration power outputs (P1 and P5) to cycling ascent performance (VAM_{P20}). Model diagnostics were performed to verify assumptions of linearity, normality of residuals, and homoscedasticity.

3. Results

All 12 participants completed the cycling and strength tests. Two participants were identified as potential outliers according to the interquartile range criterion, but no data points were removed as they were considered to reflect distinct performance profiles rather than implausible values. Additionally, sensitivity analyses were conducted excluding these participants, which did not result in meaningful changes in the observed relationships. Cycling performance and strength-related data results are presented in Table 1.

The correlation matrix is presented in Figure 1. Strong associations were observed among cycling performance variables, with P1 showing a very large correlation with P5 ($r = 0.89$, $p < 0.001$) and P20 ($r = 0.86$, $p < 0.001$) (Figure 1). P5 also presented an extremely large correlation with P20 ($r = 0.94$, $p < 0.001$). VAM_{P20} showed a very large positive association with P5 ($r = 0.86$, $p < 0.001$) and with P1 ($r = 0.81$, $p = 0.001$). In contrast, relationships between VAM_{P20} and strength-related variables were weak or trivial, including v_0 ($r = 0.09$, $p = 0.79$) and 1RM_rel ($r = -0.11$, $p = 0.73$). Strong associations were observed among strength-related variables derived from the load–velocity profile. Maximal theoretical load (C_0) showed an extremely large positive correlation with relative strength (1RM_rel; $r = 0.94$, $p < 0.001$) and a very large association with the slope of the L-V relationship ($r = 0.88$, $p < 0.001$). Similarly, 1RM_rel was very largely correlated with the L-V slope ($r = 0.84$, $p < 0.001$). In contrast, maximal theoretical velocity (v_0) showed trivial to moderate and non-significant associations with the rest of the strength-related variables (r range: -0.53 to 0.25, $p > 0.05$).

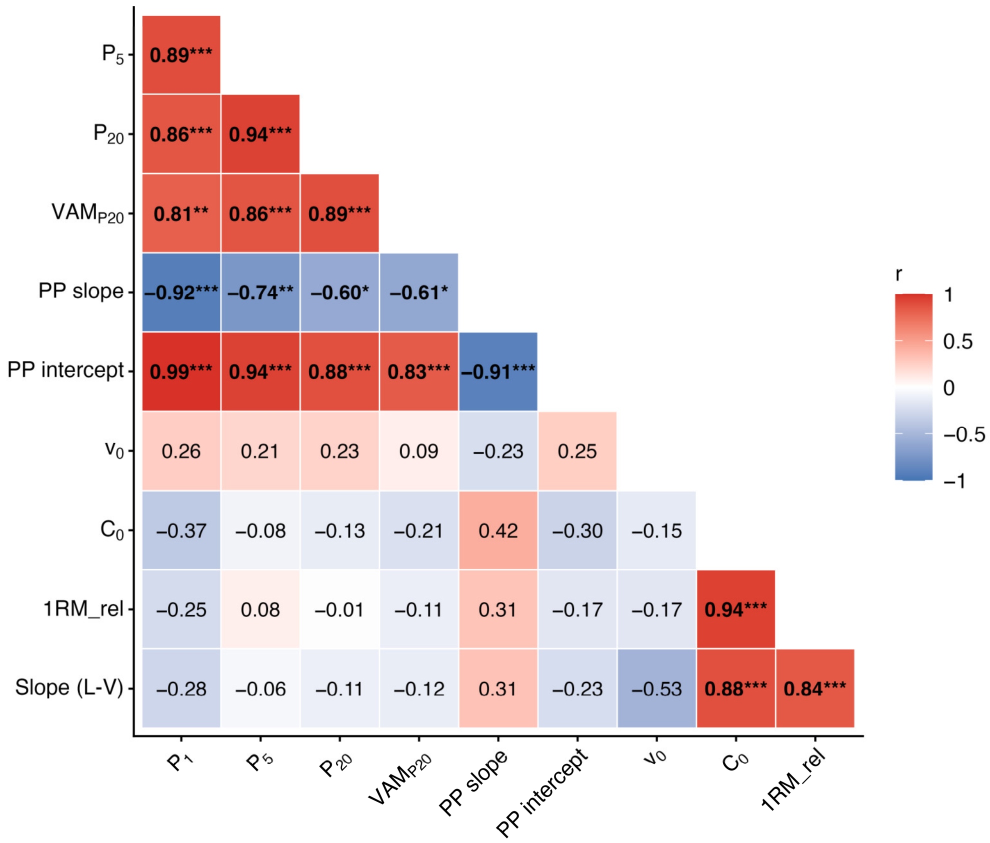

Figure 1. Correlation heatmap of cycling performance (P1, P5, P20, VAM_{P20}, PP slope, and PP intercept) and strength-related variables (v_0, C_0, 1RM_rel, and L-V slope). Colors represent Pearson correlation coefficients (r), with red indicating positive correlations and blue indicating negative correlations. Significant values are shown by symbols (* $p < 0.05$, ** $p < 0.01$; *** $p < 0.001$). P1, P5, and P20: peak power output at 1, 5, and 20 min ($W \cdot kg^{-1}$), respectively; VAM_{P20}: mean ascent velocity in P20 ($m \cdot h^{-1}$); PP: cycling power profile; v_0: maximal theoretical velocity; C_0: maximal theoretical load; 1RM_rel: one-repetition maximal relative strength; L-V: half squat load–velocity relationship.

The relationships between cycling ascent performance and derived strength-related and cycling PP variables are presented in Figure 2. These analyses confirmed the strong influence of cycling-specific variables (Cycling PP slope vs. VAM_{P20}: large negative correlation, r = −0.61, $p < 0.034$; Cycling PP intercept vs. VAM_{P20}: very large positive correlation, r = 0.83, $p < 0.001$), while derived strength-related variables showed weak or trivial non-meaningful associations (C_0 vs. VAM_{P20}: r = −0.21, $p = 0.51$, Slope (L-V) vs. VAM_{P20}: r = −0.12, $p = 0.71$).

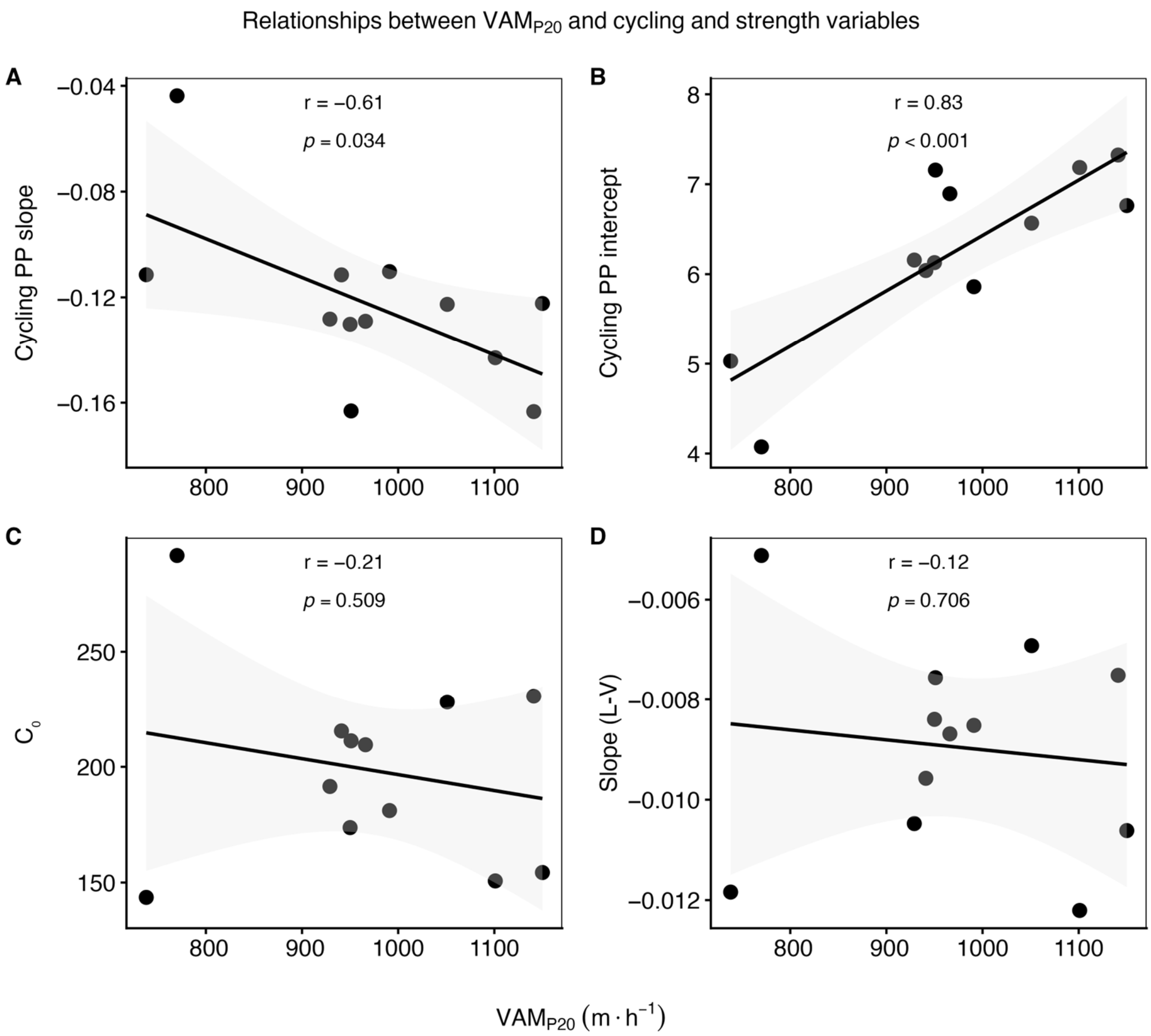

Figure 2. Relationships between mean ascent velocity (VAM_{P20}) and selected cycling-specific and strength-related variables. (**A**) Relationship between VAM_{P20} and Cycling PP slope. (**B**) Relationship between VAM_{P20} Cycling PP intercept. (**C**) Relationship between VAM_{P20} and C_0. (**D**) Relationship between VAM_{P20} and L-V slope. Each panel shows individual data points with linear regression lines and 95% confidence intervals. Pearson correlation coefficients (r) and corresponding p-values are displayed. PP: cycling power profile; C_0: maximal theoretical load; L-V: half squat load-velocity relationship.

Table 1. Descriptive statistics of cycling Power Profile (PP) and half squat Load–Velocity (L-V) profile.

	Variable	Mean	SD	Minimum	Maximum
Cycling Performance	P1 ($W \cdot kg^{-1}$)	6.96	1.13	4.18	8.19
	P5 ($W \cdot kg^{-1}$)	4.61	0.61	3.50	5.21
	P20 ($W \cdot kg^{-1}$)	4.02	0.51	3.01	4.61
	VAM_{P20} ($m \cdot h^{-1}$)	973.25	128.91	738.00	1150.00
	Cycling PP slope	−0.12	0.03	−0.16	−0.04
	Cycling PP intercept	6.27	0.96	4.07	7.32
Strength Performance	V_0 ($m \cdot s^{-1}$)	1.71	0.19	1.46	2.06
	C_0 (kg)	198.48	41.98	143.60	291.75
	1RM_rel	2.78	0.62	1.86	4.11
	Slope (L-V)	−0.009	0.002	−0.012	−0.005

Values are presented as mean, standard deviation (SD), minimum, and maximum. P1, P5, and P20 represent peak power outputs at 1, 5, and 20 min, respectively. VAM_{P20}: mean ascent velocity in P20; v_0: maximal theoretical velocity; C_0: maximal theoretical load; 1RM_rel: maximal relative strength; L-V: load–velocity profile.

The multiple linear regression model explained a large proportion of the variance in VAM_{P20} ($R^2 = 0.75$, adjusted $R^2 = 0.69$; $F (2,9) = 13.28$, $p < 0.01$), with a residual standard error of 71.7 $m \cdot h^{-1}$. However, neither P1 ($\beta = 22.94$, $p = 0.605$) nor P5 ($\beta = 144.08$, $p = 0.104$) showed significant independent contributions to the model (Figure 3), likely due to multicollinearity between these strongly correlated predictors. A slight increase in dispersion at higher fitted values was observed, although no systematic bias was evident. The resulting equation was:

$$VAM_{P20} = 149.2 + 22.9 \times P1 + 144.1 \times P5, \quad (1)$$

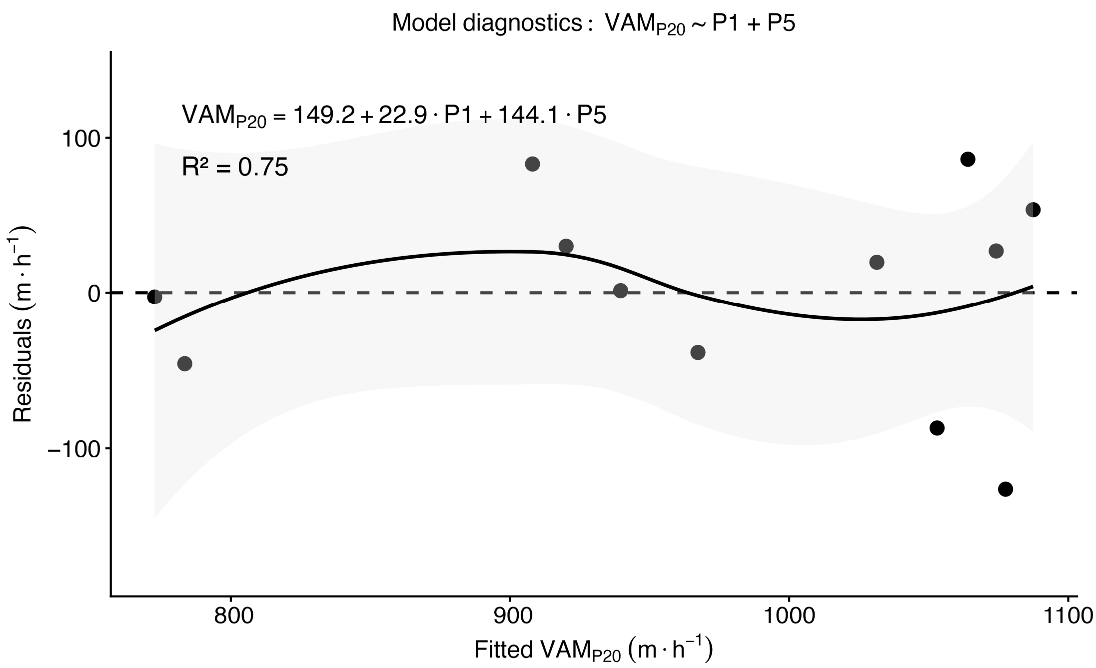

Figure 3. Residual diagnostics of the regression model predicting mean ascent velocity (VAM_{P20}) from short-duration peak power outputs (P1 and P5). The plot shows residuals versus fitted values, including a locally weighted regression smoothing line with 95% confidence interval. P1 and P5: peak power output at 1 and 5 min ($W \cdot kg^{-1}$).

4. Discussion

The present study examined the relationships between cycling performance and strength-related variables obtained from a L-V profile in masters-level cyclists. The main findings indicate that: (i) VAM_{P20} was strongly associated with cycling-specific performance variables, particularly short-duration power outputs and PP-derived metrics; (ii) strength-related variables derived from the half squat showed no significant relationships with cycling performance; and (iii) short-duration power outputs (P1 and P5) explained a large proportion of the variance in VAM_{P20}.

Despite the widespread use of the half squat in strength training and assessment for cyclists [21,24,25], the absence of meaningful association between VAM_{P20} and strength-related parameters (C_0, v_0, 1RM_rel, and L-V slope) found in this study suggests that neuromuscular characteristics assessed through non-specific resistance exercises do not directly translate into cycling performance. These findings are consistent with previous literature indicating that maximal strength is not a primary determinant of cycling endurance performance [12], despite the known benefits of strength training on cycling economy and fatigue resistance [13,25]. This reinforces the principle of specificity, whereby performance is more closely related to task-specific physiological and mechanical demands [11,18,20,23]. Neuromuscular assessments derived from non-cycling tasks may fail to reflect the coordinated, cyclic, and submaximal force production patterns that characterize pedaling technique [1,34]. However, it is possible that in upper performance levels, where all capacities are more developed and constrained, maximal strength could be more associated with aerobic performance [21]. These neuromuscular capacities may also be more closely related to short-duration efforts (e.g., sprint performance) [20,22], which further supports the rationale of the present study to examine the relationships across different durations within the cycling power profile.

Although strength-related variables were not associated with cycling performance, strong relationships were observed within the L-V profile itself. Specifically, C_0 showed extremely large correlations with 1RM_rel and the L-V slope, indicating a high internal consistency of the neuromuscular profile derived from the half squat and a force-oriented L-V profile characteristic of cycling [19,22].

The regression analysis revealed that P1 and P5 collectively explained 75% proportion of the variance in VAM_{P20}, indicating that short-duration power contributes meaningfully to overall performance capacity, despite significant differences in aerobic metabolism contribution [35]. Cycling variables derived from the PP (slope and intercept) also showed meaningful associations with VAM_{P20}, particularly the intercept, which exhibited a very large positive correlation. This confirms that parameters derived from the PP may provide valuable insights into performance capacity [9], likely reflecting the overall power production capability of the cyclist rather than isolated physiological components.

From a physiological perspective, VAM_{P20} is closely linked to maximal oxygen uptake, fractional utilization, and efficiency [12]. While neuromuscular factors may influence performance through improved force application and reduced energy cost, their contribution is likely mediated through changes in efficiency rather than direct increases in aerobic capacity. Therefore, the weak associations observed in the present study are consistent with the hierarchical organization of endurance performance, where central and peripheral aerobic adaptations dominate over neuromuscular characteristics assessed.

From an applied perspective, these findings highlight the importance of prioritizing sport-specific and aerobic-oriented assessments when evaluating performance in road cyclists. Strength L-V profiling assessments may provide valuable information regarding neuromuscular status and training adaptations, but their utility as predictors of aerobic performance appears limited. Coaches and practitioners should therefore interpret these metrics with caution when attempting to infer endurance capacity. Furthermore, while short-duration power contributes to overall performance, training interventions aimed at improving VAM_{P20} should primarily target aerobic capacity, efficiency, and fatigue resistance.

The relatively small sample size may limit the statistical power to detect subtle relationships and restrict the generalizability of the findings. Additionally, although two participants were identified as potential outliers, they were retained as they represented distinct performance profiles rather than implausible values, and sensitivity analyses confirmed the robustness of the results. Given the number of pairwise correlations performed, the potential for Type I error should be considered; therefore, individual correlations should be interpreted with caution. Future studies should include larger samples and explore different performance levels to better understand how strength adaptations influence cycling performance over time. Although reliability metrics were not directly assessed in the present study, L-V profiling during the half squat and cycling power measurements has been previously shown to be a valid and reliable method in similar populations and testing conditions [9,26,27,29].

5. Conclusions

Cycling performance in masters-level cyclists appears to be primarily determined by cycling-specific variables rather than strength-related characteristics derived from conventional strength exercises such as the half squat. These findings reinforce the importance of task specificity and highlight the multifactorial nature of endurance performance, where aerobic determinants play a dominant role.

Author Contributions: Conceptualization, F.O.-C., A.S.-G. and J.I.P.-Q.; methodology, F.O.-C., A.S.-G. and J.I.P.-Q.; software, F.O.-C., and J.I.P.-Q.; validation, F.O.-C., A.S.-G. and J.I.P.-Q.; formal analysis, F.O.-C., and J.I.P.-Q.; investigation, F.O.-C., A.S.-G. and J.I.P.-Q.; resources, F.O.-C., A.S.-G. and J.I.P.-Q.; data curation, F.O.-C., and J.I.P.-Q.; writing—original draft preparation, F.O.-C., A.S.-G. and J.I.P.-Q.; writing—review and editing, F.O.-C., A.S.-G. and J.I.P.-Q.; visualization, F.O.-C., A.S.-G. and J.I.P.-Q.; supervision, J.I.P.-Q.; project administration, F.O.-C., A.S.-G. and J.I.P.-Q. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: The study protocol was conducted in accordance with the Declaration of Helsinki and was approved by the Ethics Committee of Research in Humans of the Ethics Commission in Experimental Research of University of Valencia (ref. 2023-FIS-3176133).

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: The data presented in this study are available from the corresponding author upon reasonable request. The data are not publicly available due to privacy and ethical restrictions.

Acknowledgments: The authors would like to thank the participants for their commitment and effort during the study.

Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

PP	Power Profile
L-V	Load–Velocity
P1	1 min maximal mean power output
P5	5 min maximal mean power output
P20	20 min maximal mean power output

VAMP20	Mean Ascent Velocity
MPV	Mean Propulsive Velocity
v_0	Maximal theoretical velocity
C_0	Maximal Theoretical load
1RM_rel	Relative one-maximum repetition

References

1. Dorel, S.; Couturier, A.; Lacour, J.R.; Vandewalle, H.; Hautier, C.; Hug, F. Force-velocity relationship in cycling revisited: Benefit of two-dimensional pedal forces analysis. *Med. Sci. Sports Exerc.* **2010**, *42*, 1174–1183. [CrossRef] [PubMed]
2. Hug, F.; Dorel, S. Electromyographic analysis of pedaling: A review. *J. Electromyogr. Kinesiol.* **2009**, *19*, 182–198. [CrossRef]
3. Douglas, J.; Ross, A.; Martin, J.C. Maximal muscular power: Lessons from sprint cycling. *Sports Med.-Open.* **2021**, *7*, 48. [CrossRef]
4. Mujika, I.; Rønnestad, B.R.; Martin, D.T. Effects of increased muscle strength and muscle mass on endurance-cycling performance. *Int. J. Sports Physiol. Perform.* **2016**, *11*, 283–289. [CrossRef]
5. Quod, M.; Marti, D.; Martin, J.; Laursen, P. The Power Profile Predicts Road Cycling MMP. *Int. J. Sports Med.* **2010**, *31*, 397–401. [CrossRef]
6. Pinot, J.; Grappe, F. The record power profile to assess performance in elite cyclists. *Int. J. Sports Med.* **2011**, *32*, 839–844. [CrossRef]
7. Denham, J.; Scott-Hamilton, J.; Hagstrom, A.D.; Gray, A.J. Cycling Power Outputs Predict Functional Threshold Power and Maximum Oxygen Uptake. *J. Strength Cond. Res.* **2020**, *34*, 3489–3497. [CrossRef] [PubMed]
8. van Erp, T.; Sanders, D. Demands of professional cycling races: Influence of race category and result. *Eur. J. Sport Sci.* **2020**, *21*, 666–677. [CrossRef]
9. Leo, P.; Spragg, J.; Podlogar, T.; Lawley, J.S.; Mujika, I. Power profiling and the power-duration relationship in cycling: A narrative review. *Eur. J. Appl. Physiol.* **2022**, *122*, 301–316. [CrossRef]
10. Passfield, L.; Hopker, J.G.; Jobson, S.; Friel, D.; Zabala, M. Knowledge is power: Issues of measuring training and performance in cycling. *J. Sports Sci.* **2017**, *35*, 1426–1434. [CrossRef] [PubMed]
11. Jeukendrup, A.E.; Craig, N.P.; Hawley, J.A. The bioenergetics of world class cycling. *J. Sci. Med. Sport* **2000**, *3*, 414–433. [CrossRef]
12. Lucia, A.; Hoyos, J.; Chicharro, J.L. Physiology of professional road cycling. *Sports Med.* **2001**, *31*, 325–337. [CrossRef] [PubMed]
13. Berryman, N.; Mujika, I.; Arvisais, D.; Roubeix, M.; Binet, C.; Bosquet, L. Strength training for middle- and long-distance performance: A meta-analysis. *Int. J. Sports Physiol. Perform.* **2018**, *13*, 57–63. [CrossRef] [PubMed]
14. Dorrell, H.F.; Moore, J.M.; Gee, T.I. Comparison of individual and group-based load-velocity profiling as a means to dictate training load over a 6-week strength and power intervention dictate training load over a 6-week strength and power intervention ABSTRACT. *J. Sports Sci.* **2020**, *38*, 2013–2020. [CrossRef] [PubMed]
15. Morin, J.B.; Samozino, P. Interpreting power-force-velocity profiles for individualized and specific training. *Int. J. Sports Physiol. Perform.* **2016**, *11*, 267–272. [CrossRef]
16. Włodarczyk, M.; Adamus, P.; Zieliński, J.; Kantanista, A. Effects of velocity-based training on strength and power in elite athletes—A systematic review. *Int. J. Environ. Res. Public Health* **2021**, *18*, 5257. [CrossRef]
17. García-Ramos, A. Velocity-Based Approaches More Accurately Estimated the One-Repetition Maximum (1RM) After Four Weeks of Training Compared to Baseline and Group-Adjusted 1RM Approaches. *Appl. Sci.* **2025**, *15*, 10874. [CrossRef]
18. Rodríguez-Rielves, V.; Barranco-Gil, D.; Buendía-Romero, Á.; Hernández-Belmonte, A.; Higueras-Liébana, E.; Iriberri, J.; Sánchez-Redondo, I.R.; Lillo-Beviá, J.R.; Martínez-Cava, A.; de Pablos, R.; et al. Torque–Cadence Profile and Maximal Dynamic Force in Cyclists: A Novel Approach. *Sensors* **2024**, *24*, 1997. [CrossRef]
19. Giroux, C.; Rabita, G.; Chollet, D.; Guilhem, G. Optimal Balance Between Force and Velocity Differs Among World-Class Athletes. *J. Appl. Biomech.* **2016**, *32*, 59–68. [CrossRef]
20. Gross, M.; Gross, T. Relationship between cyclic and non-cyclic force-velocity characteristics in bmx cyclists. *Sports* **2019**, *7*, 232. [CrossRef]
21. Javaloyes, A.; Sánchez-muñoz, C.; Moya-ramón, M.; Mateo-march, M. Strength as a Predictor of Aerobic Power in Competitive Cyclists: National Team Insights. *Int. J. Sports Med.* **2025**, *47*, 356–363. [CrossRef]
22. Dunst, A.K.; Ji, S.; Wahl, P. Strength Exercise F–v and P–v Profiles as Predictors of Elite Sprint-Cycling Performance. *Int. J. Sports Physiol. Perform.* **2025**, *20*, 1745–1755. [CrossRef]
23. Kristoffersen, M.; Sandbakk, Ø.; Rønnestad, B.R.; Gundersen, H. Comparison of short-sprint and heavy strength training on cycling performance. *Front. Physiol.* **2019**, *10*, 1132. [CrossRef] [PubMed]
24. Koninckx, E.; Van Leemputte, M.; Hespel, P. Effect of isokinetic cycling versus weight training on maximal power output and endurance performance in cycling. *Eur. J. Appl. Physiol.* **2010**, *109*, 699–708. [CrossRef]
25. Rønnestad, B.R.; Mujika, I. Optimizing strength training for running and cycling endurance performance: A review. *Scand. J. Med. Sci. Sports* **2014**, *24*, 603–612. [CrossRef]

26. García-Ramos, A.; Feriche, B.; Pérez-Castilla, A.; Padial, P.; Jaric, S. Assessment of leg muscles mechanical capacities: Which jump, loading, and variable type provide the most reliable outcomes? *Eur. J. Sport Sci.* **2017**, *17*, 690–698. [CrossRef]
27. Martínez-Cava, A.; Morán-Navarro, R.; Sánchez-Medina, L.; González-Badillo, J.J.; Pallarés, J.G. Velocity- and power-load relationships in the half, parallel and full back squat. *J. Sports Sci.* **2019**, *37*, 1088–1096. [CrossRef]
28. Faul, F.; Erdfelder, E.; Lang, A.-G.; Buchner, A. G*Power 3: A flexible statistical power analysis program for the social, behavioral, and biomedical sciences. *Behav. Res. Methods.* **2007**, *39*, 175–191. [CrossRef] [PubMed]
29. Bouillod, A.; Soto-Romero, G.; Grappe, F.; Bertucci, W.; Brunet, E.; Cassirame, J. Caveats and Recommendations to Assess the Validity and Reliability of Cycling Power Meters: A Systematic Scoping Review. *Sensors* **2022**, *22*, 386. [CrossRef] [PubMed]
30. Sánchez-Medina, L.; Pallarés, J.G.; Pérez, C.E.; Morán-Navarro, R.; González-Badillo, J.J. Estimation of Relative Load From Bar Velocity in the Full Back Squat Exercise. *Sports Med. Int. Open* **2017**, *01*, E80–E88. [CrossRef]
31. Willardson, J.M. A brief review: Factors affecting the length of the rest interval between resistance exercise sets. *J. Strength Cond. Res.* **2006**, *20*, 978–984. [CrossRef]
32. García-Ramos, A. Resistance Training Intensity Prescription Methods Based on Lifting Velocity Monitoring. *Int. J. Sports Med.* **2023**, *45*, 257–266. [CrossRef] [PubMed]
33. Hopkins, W.G.; Marshall, S.W.; Batterham, A.M.; Hanin, J. Progressive statistics for studies in sports medicine and exercise science. *Med. Sci. Sports Exerc.* **2009**, *41*, 3–12. [CrossRef] [PubMed]
34. Martin, J.C.; Brown, N.A.T. Joint-specific power production and fatigue during maximal cycling. *J. Biomech.* **2009**, *42*, 474–479. [CrossRef] [PubMed]
35. Gastin, P.B. Energy system interaction and relative contribution during maximal exercise. *Sports Med.* **2001**, *31*, 725–741. [CrossRef]

https://doi.org/10.3390/app16115346