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Original Research

Maximal Cycling Intensity Compromises Upper Body Postural Stability Regardless of Experience Level

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Abstract

International Journal of Exercise Science 19(6): 6011, 2026. Stability of the body is crucial in cycling to minimize injury risk while maximizing efficiency of power transfer. The present study examined how increasing cycling intensity influences upper-body stability and whether stability differs by experience level. Twenty cyclists (8 competitive, 12 recreational) completed a graded exercise test (GXT) to exhaustion while wearing three inertial movement units (IMU) that measured the angle of the head, torso, and pelvis. Angle variance in each stage was calculated to quantify upper-body position stability across stages. Angle variance of head, torso, and pelvis angle increased with exercise intensity ($p = 0.003$, $\eta^2_p = 0.27$; $p = 0.059$, $\eta^2_p = 0.17$; $p = 0.004$, $\eta^2_p = 0.29$, respectively), but these changes did not differ between the two experience levels ($p > 0.1$, $\eta^2_p < 0.01$). Additionally, a pairwise comparison showed that the changes in angle variance mainly occurred at the final stages of the GXT. These findings suggest that maximal workloads compromise upper-body stability in cyclists, a pattern that is statistically similar across experience levels. Limitations include modest sample size (n=20) and analysis based on stage number rather than physiological intensity markers, both of which may have limited detection of experience-level differences. Future research should utilize balanced experience groups and integrate metabolic markers in the analysis.

Keywords: Kinematic variability, inertial measurement units, graded exercise test, fatigue, biomechanics

Introduction

Biomechanics plays a key role in optimizing athletic performance by refining movement mechanics, training, and athlete-environment interactions.[1] In cycling, athlete-environment interactions can have a significant impact on performance.[2] It is well known that aerodynamic drag can significantly impact performance, especially at high speeds. Hence, modifying the position of the upper body in the sagittal plane (lowering the torso and tucking in the head and arms) is often utilized to minimize frontal area to reduce aerodynamic drag. These optimizations have driven major advances in cycling events like the world hour record, where aerodynamic refinements closely correlate with record-breaking performances.[3-5]

While this focus on aerodynamics has led to innovations in equipment and position, less attention has been paid to the cyclist's ability to maintain these postures under load. Core and postural stability of the upper body may play a critical role in sustaining aerodynamically advantageous

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positions without compromising power output, increasing knee injury risk or inducing hamstring or lower back strain.[6-8] Despite this, most cycling biomechanics research has emphasized lower limb kinematics, demonstrating the important relationships between exercise intensity and lower limb kinematics,[9] and more skilled muscle recruitment patterns in more experienced cyclists.[10] The limited research in upper body kinematics of cyclists could be in part due to the high cost of motion tracking tools. However, advancements in technology have made biomechanics research much more accessible. Leomo Type-R (Leomo, Boulder, CO, USA) is an example of these new wearable motion analysis systems. The Leomo Type-R has been utilized in research and validated as a reliable tool for analyzing lower limb motion during cycling, particularly in the sagittal plane.[11]

The purpose of this study is to investigate the relationship between upper body position stability and cycling intensity. Specifically, this study aimed to quantify upper body position variability across increasing exercise intensities using the Leomo Type-R motion analysis system. In addition to this, the study aimed to compare stability across cyclists of varying experience levels, drawing on an inverse optimization framework, in which movement patterns of highly skilled individuals are observed to infer the biomechanical and physical constraints that enable efficient performance.[12] We hypothesized that increasing exercise intensity would increase upper-body position variability. We also hypothesized that more experience would lead to less body position variability.

Methods

Participants

Cyclists of varying experience levels were recruited from the local area with fliers and social media posts targeted at road cyclists. Participants were required to be between 18 and 65 years of age, have road cycling experience, and ownership of a bicycle with drop handlebars was mandatory. Participants who had known cardiovascular conditions or orthopedic limitations due to surgery or injury were also excluded. An *a priori* power analysis was conducted using G*Power 3.1.9.7 (Universität Kiel, Germany) to determine the required sample size. With a target statistical power of 0.80, alpha = 0.05, and an effect size f = 0.25 (derived from a moderate partial eta squared of 0.06),[13] a minimum sample size of 18 participants was required. Twenty road cyclists (19 males, 1 female) met the inclusion criteria and were enrolled in the study. All recruitment materials, surveys, and testing protocols were approved by the Institutional Review Board at the University of Oklahoma. This research was carried out fully in accordance with the ethical standards of the *International Journal of Exercise Science*.[14]

Protocol

Participants were invited to a single laboratory visit after completing the online screening to complete a graded exercise test (GXT) and a VO2 verification protocol. Prior to completing the tests, participants were instructed to complete four forms: an informed consent form, a physical activity readiness questionnaire (PAR-Q), a medical history questionnaire, and a cycling experience questionnaire. The cycling experience questionnaire was designed by a panel of three cycling experts to quantify training and racing history, and the participant’s perceived experience level.

Following the completion of the consent form, the participant's road bike was mounted onto a Wahoo KICKR CORE direct drive smart trainer (Wahoo Fitness, Atlanta, GA, USA) while their height and weight in bicycle clothing were measured. The GXT protocol was then programmed into a compatible training software (Zwift, San Francisco, CA, USA). The participants' own personal bicycles were used in this study to preserve the unique bicycle geometry and the preferred riding position of each participant. This was important as it allowed us to capture the participants' body position variations without interference. Additionally, the Zwift software was utilized because it displayed a virtual avatar on a monitor in front of the participant, providing a visual anchor to mimic on-road head position, increasing the ecological validity of this study. Once the participants' bike was mounted on the trainer, participants were instructed to get onto their bikes, and three Leomo Type-R inertial measurement units (IMU) were placed on the head, torso, and pelvis. The pelvis sensor was placed at the sacrum, right above the tail bone following guidelines from Leomo.[11] The head sensor was fixed on a custom headband, and the torso sensor was secured on the front of the Wahoo TICKR heart rate monitor (Wahoo Fitness, Atlanta, GA, USA) which was placed over the sternum to ensure consistent placing across participants. The IMUs collected sagittal angle of the head, torso, and pelvis at a sampling rate of 100 Hz.

The GXT began with 5 minutes of free riding as a warm-up, while the Leomo sensor connections were established and verified. Following the warmup, the software initiated the preprogrammed GXT protocol, which was programmed to start at a work rate of 1 W/kg of body weight, and increased by 0.5 W/ kg of body weight every 3 minutes until voluntary termination or failure.[15] The work rates were set to the nearest 5 watts due to software limitations.

Participants were instructed to limit atypical movements, such as reaching for water or adjusting their riding position, until the first 30 seconds of the next 3-minute stage. At the end of each stage, the participants' heart rate was recorded, and finger-sticks were done to measure blood lactate using the Lactate Plus portable lactate analyzer (Nova Biomedical, Waltham, MA, USA). Their perceived exertion was also recorded at the end of each stage with the Borg 6-20 Rating of Perceived Exertion (RPE) scale.[16] No VO_2 measurements were taken as the equipment required for breath-by-breath analysis would restrict movement.

After the termination of the GXT, participants observed a standardized 20-minute recovery period.[17] During this, participants pedaled lightly for a minimum of 3 minutes, after which, they were encouraged to rest on a provided chair. After the recovery period, participants began the VO_2 max protocol with a 5-minute warm-up. The face mask for the metabolic cart was secured onto the participant during this time. Following the warmup, the software initiated the preprogrammed ramp protocol. The starting work rate was set to the work rate of the last fully completed stage of the GXT and was also set to increase by 10 watts each 10 seconds (1 watt per second), as the minimum programmable duration was 10 seconds. Expired gas was collected and analyzed with a TrueOne 2400 metabolic cart (Parvomedics, Sandy, UT, USA) during this ramp protocol and participants were verbally encouraged until exhaustion.

Statistical Analysis

The raw 100 Hz data collected by the Leomo IMU were averaged into one second bins. To account for outliers, the first and last 30 seconds of each stage were excluded, as significant interference was expected during these periods (e.g., lactate measurements, drinking water). Additionally, body angles with values exceeding 2.5 standard deviations from the mean stage angle were flagged as outliers and excluded from analysis. Although 3 standard deviations are more commonly used, a stricter criterion was deemed more appropriate for this dataset, as variance calculations are particularly sensitive to extreme values. The stricter threshold resulted in the removal of 0.89% additional data points relative to the 3 SD threshold (n=42). Within-stage variance of the cleaned binned means was computed for the head, torso and pelvis angles. Variance was selected as the outcome variable because it directly quantifies the magnitude of angular dispersion within each intensity stage. To enable a balanced repeated measures design, only the final six stages of each participant's graded exercise test were analyzed. The final six were chosen as this was the fewest stages completed in our dataset. Anchoring to the final six stages ensured that all participants' data reflected equivalent points of relative exercise progression toward exhaustion, rather than absolute workload. This ensured all participants contributed data across equivalent test progression points, necessary for the two-way mixed-design analysis of variance (ANOVA).

Hierarchical cluster analysis was conducted to categorize participants by training experience level using responses to the cycling experience questionnaire. Parameters in this analysis included weekly training hours, race count, self-identified athlete status, and the primary purpose of cycling. Performance metrics (e.g., VO_2 Peak, power output) were excluded to ensure clustering reflected training experience rather than physiological outcomes. Total years of cycling were excluded due to its weak association with training behavior and the presence of extreme values that did not reflect current training status. A two-cluster solution was selected based on theoretical expectations and interpretability, yielding groups designated as less-experienced and more-experienced cyclists. While formal cluster validity indices (e.g., silhouette width, gap statistic) did not strongly favor a specific cluster number, the two-cluster solution provided stable group sizes and clear differentiation in training characteristics suitable for the present analysis. To evaluate differences between the two clusters, independent samples t-tests were used to compare means for continuous variables and Fisher's exact tests were used to compare proportions for categorical variables.

Separate two-way mixed-design ANOVAs were used to determine the main effects of experience level (between-subjects), the main effects of GXT stage (within-subjects), and the interaction between the two, on head, torso, and pelvis angle variance. Partial eta squared (η^2_p) was calculated to estimate effect sizes, where ≥ 0.14 represents a large effect, 0.06–0.13 a medium effect, and 0.01–0.05 a small effect.[12] Bonferroni pairwise comparisons were conducted on significant main effects revealed by the ANOVA. R software (version 4.1.1) was used for all analyses, and alpha was set at 0.05 *a priori*.

Results

The hierarchical cluster analysis revealed two distinct clusters. Compared to cluster 2, cluster 1 had a significantly lower mean weekly training volume and participated in significantly fewer races (Table 1). Therefore, cluster 1 was labelled "Recreational", and cluster 2 was labelled " Competitive".

These two groups did not differ significantly across other characteristics, which included VO2max, years of cycling experience, age, and peak power. All continuous variables are presented in Table 1. Interestingly, the groups did not report significantly different primary purposes of cycling, bike fit or self-identified athlete status (Table 2).

Table 1. Numerical participant characteristics.

	All (n=20)	Competitive (n=8)	Recreational (n=12)	*p*
Age	37.6 ± 2.7	36.5 ± 6.8	38.3 ± 15.7	0.726
VO_2Peak (ml/kg/min)	53.1 ± 7.7	56.7 ± 6.6	50.6 ± 7.6	0.074
Power at VO_2 Peak (Watts)	356 ± 88.7	361 ± 129.8	353 ± 48.4	0.868
Length of GXT (Stage)	7.2 ± 1.0	7.6 ± 0.5	7.0 ± 1.2	0.726
Time Spent Cycling per Week (hours)	7.5 ± 3.7	11.4 ± 1.5*	5.2 ± 2.3*	<0.01
Cycling Experience (years)	4.9 ± 4.7	3.1 ± 2.5	6.0 ± 5.5	0.131
Number of Races Started	9.7 ± 13.6	20.6 ± 16.5*	2.7 ± 3.7*	0.029

Note: Values are mean ± SD, * denotes significant difference between competitive and recreational cyclists ($p < .05$), determined by independent samples t-test.

Table 2. Categorical participant characteristics.

	All (n=20)	Competitive (n=8)	Recreational (n=12)	*p*
Cycles Competitively	74%	100 %	58 %	0.325
Identifies as an Athlete	84%	100%	75%	0.619
Has had a Bike Fit	79%	100 %	67 %	0.603

Note: Values are n (%). Group differences assessed via chi-square test.

In general, variance increased across stages, with larger variability observed at the head compared to the torso and pelvis (Figure 1). Exercise Intensity demonstrated a significant main effect on angular variance for the head and pelvis but not in the torso (head: $p = 0.003$, pelvis: $p = 0.004$; torso: $p = 0.059$). No statistically significant main effects of experience or experience × stage interactions were observed for any sensor location. Effect sizes for exercise intensity were large across all body locations (head: $\eta^2_p = 0.271$, torso: $\eta^2_p = 0.167$, pelvis: $\eta^2_p = 0.292$). The effect size for the interaction effect between experience and intensity was moderate in pelvis angle measurements ($\eta^2_p = 0.074$) but small for head and torso locations (head: $\eta^2_p = 0.039$, torso: $\eta^2_p = 0.048$). Main effects of experience level were negligible across all locations (head: $\eta^2_p = 0.005$, torso: $\eta^2_p = 0.008$, pelvis: $\eta^2_p = 0.002$).Bonferroni-corrected pairwise comparisons revealed that head angle variance at stage 6 differed significantly from stages 2, 3, and 4. For pelvis angle variance, stage 6 differed significantly from stages 1 and 2, and stage 5 differed significantly from stages 1 and 2. No significant pairwise differences were found for torso angle variance.

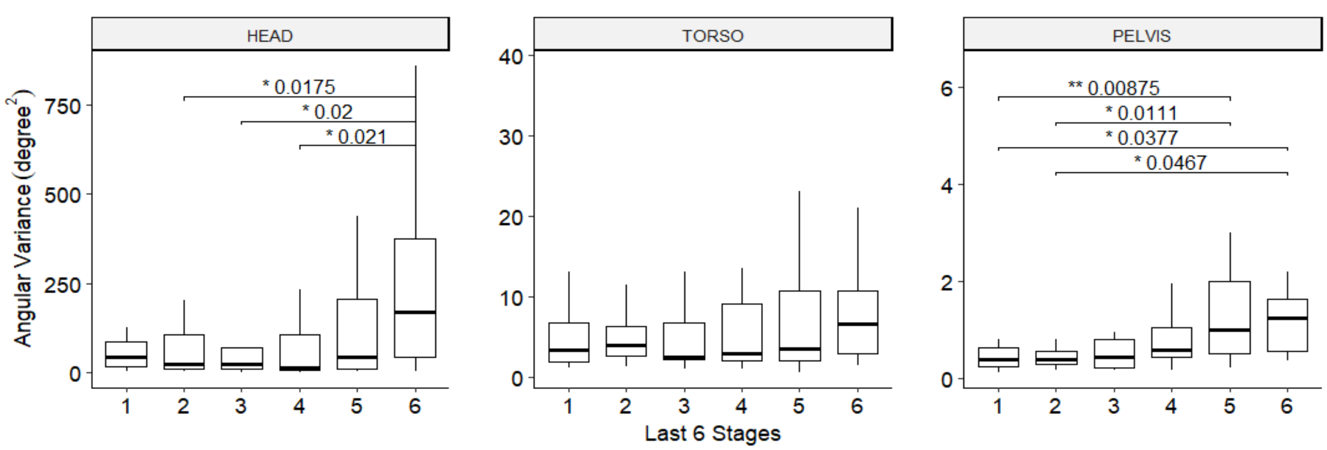

Figure 1. Pairwise Stage Comparisons of Head, Torso and Pelvis Angle Variance.
Note. Horizontal brackets indicate statistically significant pairwise differences between stages following post-hoc analysis. Exact p-values are displayed above each bracket; asterisks denote significance levels: * p < .05, ** p < .01, *** p < .001.

Discussion

The present study aimed to investigate the effects of cycling intensity on upper body position stability and to compare upper body position stability between cyclists of differing experience levels using wearable motion capture technology. We hypothesized that increasing cycling intensity would decrease upper body position stability, and that more experienced cyclists would demonstrate greater stability compared to less experienced cyclists. Our findings demonstrated that increasing cycling intensity is associated with measurable changes in upper body position stability, as assessed by angular variance at the head, torso, and pelvis. However, the results did not show any statistically significant differences between the two experience levels. Therefore, we can accept the hypothesis that increases in exercise intensity decrease stability but we reject our hypothesis that more experience leads to increased stability.

Relationship between body position variance and exercise intensity

Our results revealed that body position variance increased with intensity, with the changes mainly occurring at the highest exercise intensity stage (Figure 1). The increased variance of head, torso, and pelvis angles at higher intensities reflects fatigue-induced impairment of postural control[18,19] and the skewed nature of the data may suggest that compensatory mechanisms maintain stability until a critical fatigue threshold is exceeded. Our finding aligns with previous research demonstrating that higher exercise intensities alter lower limb kinematics, including joint angles and range of motion,[9,20,21] as well as lumbar, thorax, and elbow angles.[22] While these studies focused on mean angle changes, examining angle variance rather than mean angle provides complementary insight into postural control and movement consistency. This is particularly relevant for upper body posture, where stability affects both aerodynamic positioning and the mechanical efficiency of power production.[23] Therefore, by quantifying positional variability, our findings extend existing kinematic research to include the dimension of postural stability under metabolic stress.

Lack of difference between experience levels

Comparisons of head, torso, and pelvis angle variance between experience groups revealed no statistically significant differences. This lack of group differences was unexpected, as postural control is often cited as a key differentiator between elite and novice cyclists.[24,25] These results suggest that high-intensity cycling may compromise postural stability similarly across experience levels, or that upper body postural control under maximal effort conditions has limited trainability through typical endurance training protocols.

Several factors may explain the absence of statistically significant experience effects. First, postural stability at maximal intensities may require specific training focused on maintaining control under severe metabolic stress, and this type of specific training may be equally limited across experience levels in our sample. Second, substantial individual variation in postural control strategies may obscure group-level differences. This parallels findings from other research showing that while individual variance in pelvic and lower limb kinematics trended higher in novice cyclists compared to elite cyclists, these differences did not reach statistical significance.[10] Additionally, the features selected for hierarchical clustering successfully differentiated groups on physiological and behavioral dimensions but may not capture the specific neuromuscular adaptations underlying postural control.

Despite these results, visual inspection of the data suggests potential trends worthy of future investigation (Figure 1). The recreational group exhibited greater variance in torso angles at higher intensities and greater head variance at the final stage compared to the experienced group. Though the current method of analysis revealed the similarities between the body position variance across most of the stages, it is possible that these similarities masked the difference that occurs at maximal intensity. These observations suggest that statistically significant body position variance differences may exist, but only during maximal intensity.

The primary limitation of this study is the modest sample size (n = 20), which limits statistical power to detect effects, particularly for between-group comparisons. While sufficient power was achieved to detect the main effect of intensity, the sample size may have been insufficient to identify experience-level differences if those effects are small to moderate in magnitude. The unequal group sizes (n = 12 less-experienced, n = 8 more-experienced) resulting from cluster analysis further reduced power for between-group comparisons. Additionally, the sample was predominantly male (male = 19, female = 1), reflecting recruitment challenges rather than intentional exclusion. This skewed sample limits the generalizability of findings to female cyclists.

Analysis was restricted to the final six stages of each participant's graded exercise test to enable balanced repeated measures ANOVA design. While this approach ensured all participants contributed data at equivalent positions in their test progression, it does not standardize for absolute power output or relative physiological intensity. Consequently, the same stage number could represent different metabolic demands across participants of varying fitness levels, which may have obscured experience-related differences if postural control deteriorates at different relative intensities between groups. An alternative approach comparing across individualized intensity zones rather than stage number, as seen in similar studies[20] would have enabled more precise physiological comparisons. However, this comes at the cost of the stage-by-stage granularity provided by our method.

Finally, while IMU-based motion capture system successfully quantified upper body angular variance, this approach does not directly measure the functional consequences of postural instability, such as changes in aerodynamic drag or mechanical power transfer efficiency.

Practical Application

The observed decline in upper body postural stability at high intensities has implications for both performance optimization and injury prevention in cycling. Reduced trunk stability at high intensities may compromise cycling performance increases aerodynamic drag, which becomes progressively more important at higher speeds where drag forces dominate total resistance.[5] Additionally, because the trunk serves as a stable platform for effective force transmission from the upper body to the pedals and increased postural variance may indicate compromised mechanical efficiency thereby inducing suboptimal force transfer.[7,26] While our study did not directly measure power output efficiency or aerodynamic drag, the magnitude of variance increases at maximal intensities suggests these effects should be investigated further. This is especially relevant for competitive scenarios where races are often decided at sustained high intensities or during maximal sprint efforts where again, aerodynamic drag matters the most.

Beyond performance, fatigue-induced postural instability may have injury prevention implications. Bini et al demonstrated that kinematic alterations from high-volume cycling training can predispose cyclists to chronic lower limb injuries.[27] While their focus was on knee pain resulting from altered lower limb mechanics, it is plausible that upper body instability at high intensities may similarly increase injury risk, particularly for the lower back. Cycling-related lower back pain is highly prevalent among cyclists, and loss of trunk postural control under fatigue may contribute to excessive spinal loading or altered movement patterns that accumulate over training sessions.[24] The threshold effect observed in our data where variance increased dramatically only at the highest intensities suggests that injury risk may be particularly elevated during race-pace efforts or high-intensity interval training.

Finally, these findings also have implications for training program design. The dramatic increase in instability at maximal intensities suggests that cyclists who compete at high intensities may benefit from sport-specific core stability training under fatigued conditions, when postural control is most compromised. Given that aerodynamic drag increases exponentially with speed, maintaining stable positioning during race-pace efforts could yield meaningful performance benefits. Additionally, improved postural control may mitigate lower back injury risk, a common concern among cyclists.[24] However, the lack of experience-level differences suggests traditional training may not adequately develop this capacity, warranting investigation of targeted interventions.

Overall, these findings challenge the common belief that more training (time spent riding) leads to improved stability. This study found that at most intensities, the differences in body angle stability between competitive and recreational cyclists are minimal and may suggest that more specific training approaches might be necessary to increase stability.

This study also found that changes to body position stability mostly occur near or at maximal intensity efforts. Future studies should take this into consideration when reducing the granularity of data for analysis (e.g., summarizing to below LT1, between LT1 and 2, above LT2) to avoid masking meaningful differences.

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