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Quantifying Braking Behavior in Cyclists Using Smartphone Sensors: A Comparative Analysis of Novice and Experienced Riders

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Abstract - *Braking skill is central to safe and fast cycling, yet it is rarely quantified outside controlled labs. We used a smartphone-based inertial measurement unit (IMU) and GPS to capture real-world deceleration during a standardized maneuver performed by multiple riders of known experience. Acceleration time series were smoothed and segmented into four phases—Approach, Braking, Cornering, and Recovery—via thresholding and peak detection. From these, we derived phase durations, peak deceleration, time-to-peak, and a post-braking damping ratio computed from logarithmic decrement. Riders were aligned by (i) first brake onset, (ii) peak decel, and (iii) relative ride time to enable inter-subject comparison. Group summaries and visualizations (radar/spider plots, scatter plots, correlation heatmaps, and small multiples) reveal that experienced riders tended to brake more decisively (shorter braking duration, earlier time-to-peak) and exhibited higher damping ratios (smoother recovery), while novices showed larger, more variable peak decelerations. The pipeline is low-cost and replicable, enabling classroom-scale studies and coach feedback. Implications for rider training and safety are discussed.*

Key Words: bicycle braking; smartphone IMU; inertial sensors; acceleration analysis; time-to-peak deceleration; damping ratio; logarithmic decrement; phase segmentation; cycling safety; novice vs experienced; field study; coaching analytics

1.INTRODUCTION

Effective braking is a hallmark of proficient cycling because it governs entry speed, cornering stability, and crash avoidance. Most prior work on bicycle braking has focused on hardware or controlled tests (e.g., brake systems, stopping distances) rather than rider-specific control strategies in the wild. Recent studies have quantified bicycle stopping performance under different brake configurations and surfaces, reporting mean decelerations on the order of ~2–5 m/s^2 depending on conditions [1–3]. Complementary strands of research validate consumer-grade sensors for sports biomechanics, with inertial units enabling high-frequency motion capture at low cost [4–6], and smartphone GPS offering ~7–13 m median horizontal error in urban settings—adequate for coarse trajectory context but not for fine alignment [7]. Perception–action research further suggests distinct braking styles (late/aggressive vs early/conservative) linked to experience [8].

We propose and validate a field pipeline that (i) segments the braking maneuver into four interpretable phases, (ii) extracts comparable features across riders, and (iii) contrasts novice vs experienced groups. We also introduce a post-braking damping ratio (from logarithmic decrement) as a candidate stability metric.

Contributions. (1) A practical, fully reproducible analysis using only smartphone sensors; (2) a four-phase segmentation with multi-anchor alignment; (3) group-level comparisons and visualizations suitable for coaching dashboards; (4) an annotated dataset template and reporting checklist to support classroom replication.

2. METHODOLOGY

2.1 Participants and Apparatus

This study involved multiple volunteer riders who self-reported their cycling experience level. The cohort was divided into an Experienced group (n = 11 riders, including the author) and a Novice group (n = 9 riders). All riders performed the same standardized braking maneuver under similar environmental conditions. The test scenario was a short straight approach leading into a low-speed turn, requiring the rider to brake before and through the corner. Each rider was instructed on the course and asked to execute the braking as they normally would given the turn.

To ensure consistency, all riders used the same bicycle during the trials: a Trek Roscoe 8 hardtail mountain bike (aluminum frame, ~4 years old) weighing approximately 14.2 kg. The bike was equipped with 27.5 × 2.8″ Maxxis tires inflated to 35 PSI (the maximum recommended pressure). Maintaining high tire pressure helped minimize rolling resistance differences and ensured that sluggish tire effects did not confound the results. The seat height was kept fixed at about 38″ (96.5 cm) for all riders – a compromise height that all could use – to eliminate seat position as a variable influencing balance or braking posture. In other words, every participant rode under virtually identical bike setup and surface conditions, isolating rider behavior as the primary source of variation.

2.2 Data Collection

A smartphone (placed securely on the bike) running a sensor-logging app recorded tri-axial acceleration and GPS data throughout each run. The accelerometer was the main sensor of interest; we treated its Y-axis (or longitudinal axis aligned with the bike's direction of travel) as the measure of forward acceleration/deceleration. The sensor sampling rate was approximately 50 Hz (determined from time stamps). GPS data (latitude/longitude at 1 Hz) was recorded to provide coarse spatial context (such as identifying the segment of the ride or mapping the course), but it was not used for precise timing due to its limited accuracy (~7–13 m error)[2][7]. Instead, the inertial data served as the time base for detecting braking events and phases. All sensor data were exported as timestamped CSV files for analysis.

2.3 Signal Processing and Segmentation

First, we cleaned the raw acceleration data: we sorted by time, removed non-numbers and obvious spikes, and then smoothed the forward (Y-axis) acceleration using a simple moving average over 100 samples (about 2 s at 50 Hz). This makes the curve less noisy. For plotting only, we also made a downsampled copy (~10 Hz) so the graphs are easier to read. All final measurements were done on the full-resolution data.

Using the smoothed acceleration ( ), we marked three key moments and then labeled four phases (see Fig-1 and Fig-2 in Results):

Brake Onset: the first time ( ) drops below = $-1.5 m/s^2$. This is where real braking starts.

Peak Deceleration: the time when ( ) is most negative (the hardest braking).

Recovery Point: the first time after the peak when ( ) rises above = $-0.3\ m/s^2$. That's when braking is basically over.

With those three times, we label the timeline: Approach: start → brake onset, Braking: brake onset → peak decel, Cornering: peak deceleration → recovery point, Recovery: recovery point → end

If a rider never gets back above the recovery threshold before the file ends (for example, they keep lightly braking), the Cornering phase just runs to the end. These labels give us a simple, consistent way to compare how riders brake and how quickly they settle afterward.

2.4 Feature Extraction

From this data, we extracted a set of features for each ride:

Phase Durations: The time span (in seconds) of each phase – Approach duration, Braking duration, Cornering duration, and Recovery duration. These quantify how long the rider spent in each part of the maneuver. For example, a shorter braking duration might indicate a more abrupt, decisive braking action.

Peak Deceleration: The minimum acceleration value achieved (in m/s^2, a negative number since it's deceleration). This measures braking intensity. A more negative peak deceleration implies the rider braked harder.

Time to Peak: The time elapsed from brake onset to the peak deceleration. This indicates how quickly the rider ramps up to maximum brake force after initial brake engagement. A shorter time-to-peak suggests a rapid, decisive braking, whereas a longer time-to-peak might indicate a gradual braking or a delay in reaching full brake.

Damping Ratio: After the peak deceleration, the acceleration signal often oscillates or "settles" as the rider finishes the maneuver (for instance, the bike's suspension may bounce, or the rider may make small corrective accelerations). We computed a damping ratio ζ from these post-peak oscillations, using the logarithmic decrement method, we calculate:

$$\zeta = \frac{\delta}{\sqrt{4\pi^2 + \delta^2}}$$

Here, δ (delta) is the logarithmic decrement—the natural log of the ratio of two back-to-back post-peak acceleration amplitudes ($\delta = \ln(x_1/x_2)$), telling how quickly the bounce dies out.

This formula comes from standard linear damping theory for lightly damped systems [9–11]. In practice, ζ provides a unitless measure between 0 and 1 (critical damping) indicating how quickly the oscillations decay: higher ζ means quicker damping (a smoother return to steady state). If the acceleration trace did not exhibit a clear oscillatory decay (for example, if the rider's braking ended so smoothly that no overshoot occurred), we marked ζ as not applicable (N/A) for that run.

All these features were aggregated into a summary table for comparison (see Results). Notably, the damping ratio is an unconventional metric in cycling but potentially insightful for characterizing a rider's smoothness or bike handling in the recovery phase. The use of logarithmic decrement assumes the deceleration rebound can be approximated as an underdamped oscillation of the system (bike + rider).

2.5 Alignment and Comparative Analysis

Because riders started braking at different moments, we re-indexed each rider's time series three ways to compare them fairly: (A) onset-aligned: set time zero at the first sample where the smoothed acceleration drops below the brake threshold (a(t) < Tb); (B) peak-aligned: set time zero at the global minimum of the smoothed acceleration (the hardest brake); and (C) relative-time: map each file's timeline to τ in [0,1] using τ = (t − t_start) / (t_end − t_start). We used these alignments to create diagnostic overlays during analysis. The figures in this paper focus on feature-level comparisons (for example, braking duration, time-to-peak, peak deceleration, damping ratio) computed from the detected events and therefore do not require time-series overlays. If preferred, the relative-time normalization can be defined up to the recovery event by replacing t_end with t_recovery.

3. RESULTS

3.1 Individual Braking Profiles

In mapping out the data, we can make direct comparisons and contrasts between the two types of riders. Specifically, we can utilize the graph in Fig-1, which illustrates the relationship between longitudinal acceleration vs time for an experienced rider (Shrijat) for the duration of the turn. The vertical lines represent the phase boundaries, being onset, peak declaration, and recovery, and the regions have been color coded in accordance. Fig-2 shows the same data for a novice rider (Aadi). Numerous differences in data can be observed from these two riders. The experienced rider had achieved a peak deceleration of roughly -3.4 m/s_2 promptly after they began braking (approximately 0.8 - 1.0 seconds after brake onset).

However, by contrast, the novice rider had a much lower peak deceleration, of around -2.9 m/s_2, and occurring much later, nearly 7.5 seconds after the braking onset, or right at the entrance of the turn. Simply put, the novice rider had decided to make an overall slow descent down the slope while the experienced rider anticipated going faster and braking harder at an earlier point. Another thing to mention is that the experienced rider had a much shorter braking duration (under 1 second) compared to the novice rider braking more extensively (over several seconds). The experienced rider went on to have a short recovery time of nearly 1.8 seconds, with a smooth graph for the recovery section. The novice rider however, continued their deceleration, allowing for a longer cornering phase, and they had ended up taking longer to stabilize after the turn. These differences illustrated a general pattern that experienced riders braked in brief sharp bursts followed by quick stabilization while novice riders took a generally slow approach to the turn, braking continuously and achieving a peak deceleration at a later time.

In summary, the novice rider takes a conservative braking approach, with early and continuous braking, while the experienced rider takes aggressive and controlled braking, which falls in line with the expected "early vs late braking" styles that different skill level riders take [8].

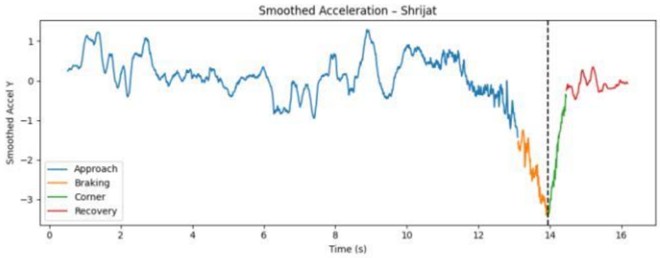

Fig-1: Longitudinal (Y) acceleration vs time for an experienced rider. The maneuver is segmented into Approach (blue), Braking (orange), Corner (green), and Recovery (red). The dashed vertical line marks Peak Deceleration. Units: acceleration in m/s^2; time in s.

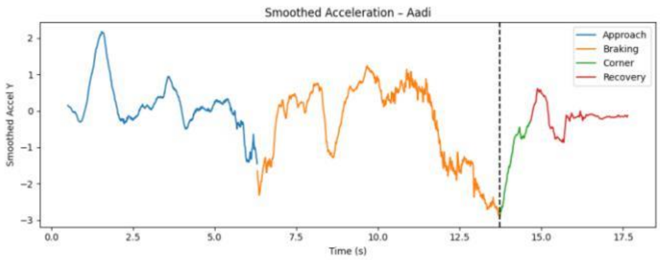

Fig-2: Longitudinal (Y) acceleration vs time for a novice rider with the same four-phase labels as Fig-1. The dashed vertical line marks Peak Deceleration. Units as in Fig-1.

Moving beyond individual cases, Figure-3 plots Braking Duration vs Peak Deceleration for all rider trials. Each point represents one run, with markers coded by experience group (e.g., orange for experienced, blue for novice). A clear clustering is evident: novice riders generally occupy the upper-left region (longer braking durations combined with highly negative peak decels), whereas experienced riders cluster toward the upper-left (shorter braking durations and milder peak decels). For example, one novice (Arjun) had an extremely long braking period (over 5 s) and also achieved one of the most severe decelerations (peak ~−4.8 m/s^2), placing him in the far lower-right corner of Fig-3. Such extreme values were not observed among the experienced group – none of the experienced riders exceeded about −3.4 m/s^2 in peak deceleration, and their braking durations were all under ~1.0 s. In general, novices showed both higher variability and a tendency toward the "worse" end of each metric (longer braking and larger deceleration magnitude), while experienced riders were more consistent and moderate. This inverse relationship between braking time and decel intensity hints at different braking strategies: some novices likely compensate for lack of braking confidence by dragging the brakes (long duration) yet still occasionally panic-brake hard (large decel), whereas experienced riders modulate their braking more efficiently (a quick but controlled deceleration).

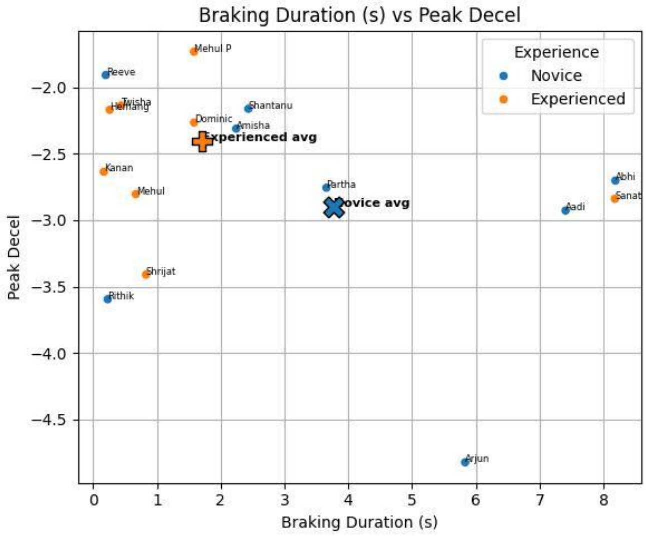

Fig-3: Scatter of Braking Duration (s) vs Peak Deceleration (m/s^2) for all riders, colored by Experience. The "Novice avg" (X marker) and "Experienced avg" (plus marker) show cohort means. More negative values indicate harder braking.

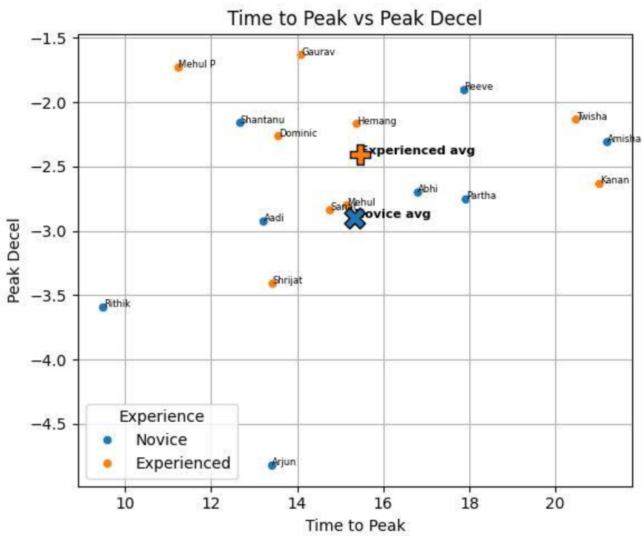

Fig-4: Scatter of Time to Peak (s)—elapsed time from brake onset to peak—vs Peak Deceleration (m/s^2). Points colored by Experience. Cohort means shown as Novice avg (X) and Experienced avg (plus).

Another important aspect is time-to-peak vs intensity, shown in Figure-4 (Peak Deceleration plotted against Time to Peak). Here too we see a dichotomy: experienced riders reached their peak decel very quickly after brake onset (often in under 1 s), whereas novices had a wide range of times-to-peak, including many taking 5–8 s before hitting maximum braking. The experienced group's points cluster on the left side of Fig-4 (short time-to-peak), mostly with moderate peak decel values (around –2 to –3 m/s^2). The novice points scatter to the right, with some still only reaching mild decel (around –2 m/s^2 even after many seconds of braking) and others eventually reaching very high decel (–4 to –5 m/s^2) but only after a long delay. This indicates variability in novice behavior: some brake too timidly (never achieving a high decel at all), while others may hesitate then suddenly brake hard at the last moment.

By contrast, all experienced riders consistently achieved a significant deceleration quickly, implying a more decisive braking action. This metric, Time-to-Peak, is essentially quantifying a rider's braking aggressiveness or decisiveness. We found that on average the experienced riders had a time-to-peak roughly an order of magnitude shorter than novices. For instance, among experienced riders the typical onset-to-peak interval was <1 s (with some as low as ~0.2–0.5 s), whereas novices often took several seconds (in one case ~7–8 s). This quantitative evidence strongly supports the idea that experienced riders employ a "late braking" strategy – they approach the turn at speed and then very quickly brake to scrub speed at the last possible moment – whereas novices lean toward an "early braking" strategy, starting to slow down well before the turn and taking longer to reach whatever peak decel they are comfortable with.

Fig-5: Scatter of Corner Duration (s) vs Damping Ratio (ζ) computed via logarithmic decrement from post-peak oscillations. Points colored by Experience with Novice avg (X) and Experienced avg (plus). Low ζ (~0) indicates little or no measurable oscillatory recovery.

We also investigated the relationship between how long a rider spends cornering (coasting/braking through the turn) and their post-braking stability, via the Corner Duration vs Damping Ratio plot in Figure-5. Interestingly, we did not find a very tight correlation, but there is a noticeable trend: riders who had prolonged cornering phases tended to exhibit very low damping ratios (near zero). In Fig-5, a cluster of points with long Corner durations (>~3 s) all have ζ values close to 0–0.02 (essentially negligible damping ratio). Many of these points correspond to novice runs where the rider possibly continued to brake lightly through the entire turn and never produced a distinct oscillatory "rebound"—in effect, they might have eased off so gradually that the acceleration simply returned to zero without a noticeable overshoot. In contrast, riders who completed the corner phase more quickly (short corner durations) sometimes show higher damping ratios. One experienced rider in particular (Mehul) stands out with a damping ratio around ζ = 0.4 and a very short cornering time; in this case, the acceleration trace exhibited a couple of small oscillations after the peak decel which decayed rapidly (hence a high ζ). Generally, higher ζ values (say ζ > 0.2) were only observed among the experienced group, and these were associated with quick stabilization post-peak. Low ζ (near

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zero) was common in novices, some of whom had extended deceleration tails and essentially no oscillatory recovery (the bike/rider took a long time to settle, or remained in an altered state through the turn). Thus, Fig-5 suggests that a higher damping ratio correlates with a more assertive “hit the brakes and recover” style, whereas a prolonged corner phase (often a sign of tentative braking) yields little measurable damping because the rider never lets the bike freely rebound. Although the correlation is not strong in a linear sense (damping ratio had generally low correlation with other variables, as we’ll see next), this comparison is conceptually useful: it reinforces that damping ratio is capturing something about how smoothly and quickly the rider returns to steady state.

Figure-6 presents the correlation matrix for all pairs of computed features across the dataset. One striking relationship is between Approach Duration and Braking Duration, which show a strong negative correlation (r ≈ –0.70 in our cohort). This makes intuitive sense and matches our earlier observations: riders who carried speed longer (long approach time) tended to brake in a shorter burst, whereas those who started braking early (short approach) ended up with a long drawn-out braking phase. In other words, there appears to be a strategy trade-off – either you approach fast and do a quick heavy brake, or you begin slowing early and take a long time to brake. Our data shows this trade-off clearly (r ~ –0.7). Another noticeable correlation (moderate in magnitude) is a negative correlation between Braking Duration and Peak Deceleration (approximately r ≈ –0.34). This suggests that riders who braked for a long time generally did not reach the highest deceleration peaks, whereas the highest peak decels were often achieved in shorter braking intervals. This too aligns with the idea that a confident, quick braking action results in a sharper deceleration spike. We also see a mild positive correlation between Approach Duration and Peak Decel (r ~ +0.4), meaning longer approach (late braking) is associated with less extreme decel (because experienced riders who wait later actually modulate brakes to avoid going insanely hard, whereas some novices who started braking early still hit only moderate decel). Many other feature pairs show little to no linear correlation. Notably, the Damping Ratio (ζ) has weak pairwise correlations with all other metrics (|r| < 0.2 in every case on Fig-6). This indicates that ζ is largely independent – it measures an aspect of performance (smoothness of recovery) that is not inherently linked with, say, how hard or how long someone braked. For example, one might assume a rider who brakes very hard would have a lot of oscillation (low damping) – but we found that’s not universally true; some riders braked hard and still stabilized quickly. The independence of damping ratio suggests it provides complementary information: it could be a unique indicator of rider skill relating to bike handling and balance during recovery, separate from the pure timing and intensity of braking.

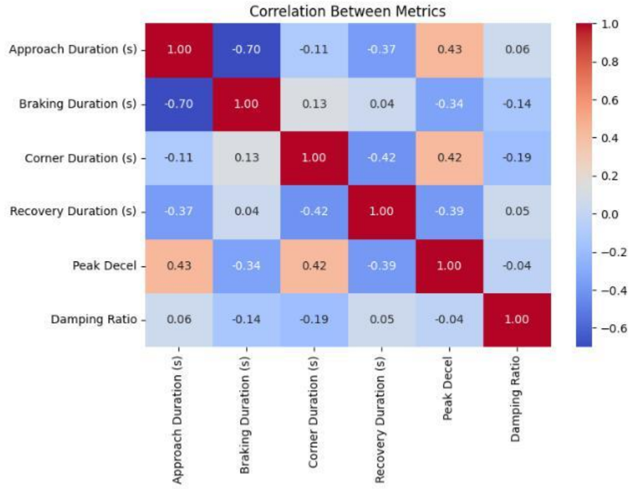

Fig-6: Pearson correlation matrix across extracted features: Approach Duration, Braking Duration, Corner Duration, Recovery Duration, Peak Deceleration, Damping Ratio. Values annotated (−1 to +1). Strong negative correlation between Approach and Braking durations highlights a strategy trade-off.

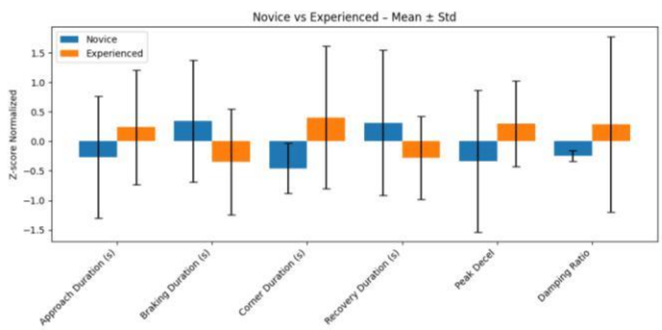

Fig-7: Group comparison of z-score normalized metrics with mean ± standard deviation for Novice and Experienced cohorts. Experienced riders show shorter Braking/Recovery durations and higher Damping Ratios on average.

We finally compared the average performance of the two groups per each key metric. Figure-7 (to be inserted) summarizes the mean values for experienced vs novice riders across several features, after z -score normalization (so that differences can be compared on a common scale). Additionally, positive values indicate above the grand mean and negative below (error bars representing standard deviations). According to the chart, the experienced group had scored above the mean on Damping Ratio, and lower on Braking Duration and Recovery Duration. Essentially, experienced riders on average had a higher damping ratio and spent less time braking and less time recovering from the turn than novice bikers did. The novice bikers, on the other hand, had a tendency towards longer Braking and Recovery durations as well as lower damping ratios. It should be noted that novices also showed shorter Approach durations than experienced riders on average, which is consistent with the novices braking earlier, and they also had more negative Peak Decel values. Despite the limited sample size, these differences align with the hypothesis that experienced riders will brake smoother and quicker. Experienced riders will make a more efficient maneuver, waiting longer into the turn, applying the brakes for a shorter time, and achieve necessary deceleration without exceeding that amount, for a faster recovery at the end. Novices, aggregately, will spend more time in braking and recovery as well as braking more harshly (likely out of anxiety), which results in less controlled braking behavior. As an experienced rider, I can confirm that this anxiety will only go away as one attempts more similar turns. Fig-7 has error bars that indicate that novices also had higher variability in most metrics (specifically peak decel and braking time), whilst experienced riders will be more consistent amongst themselves. This consistency could reflect a common understanding of braking technique that novices are yet to internalize.

4. DISCUSSION

The analysis shows clear differences between novice and experienced riders. Results match common riding advice and earlier studies, and the new metrics like time to peak and damping ratio help describe these differences in a measurable way.

Novices often brake for longer and sometimes hit very large deceleration peaks. One novice reached about -4.8 m/s^2 while braking for more than 5 s. Experienced riders usually show short braking with milder peaks, often around -2 to -3 m/s^2. Very hard front braking can cause slip or rear lift, so skilled riders avoid pushing that limit [2][3][1–3][12]. This pattern fits our data and suggests better modulation among experienced riders.

Experienced riders tend to reach peak decel soon after the brakes start, often within the first second. Novices take much longer. This supports the idea of two styles: late and decisive versus early and gradual [8]. The late style is not reckless here. Riders still reach the needed decel in time, which likely comes from better feel for traction and corner entry speed.

After the peak, some runs show a small bounce in acceleration before settling. The damping ratio ζ estimates how quickly that bounce fades. Many runs have very low ζ, sometimes because there is no clear bounce at all. On average, experienced riders show higher ζ, but not always. A few novices have long cornering with near-zero ζ, which suggests slow settling or continuous light braking. ζ does not track strongly with other metrics, so it adds a different view of control smoothness.

Approach time and braking time are strongly negatively correlated in this sample. Riders who carry speed longer tend to brake for a shorter time, and those who start braking early tend to brake for longer. Braking time and peak decel show a moderate negative correlation. Shorter braking windows are linked with sharper peaks. These patterns are useful for coaching because they link simple choices in timing to measurable outcomes.

The analysis shows clear differences between novice and experienced riders across intensity, timing, and recovery. Novices often brake for longer and sometimes hit very large deceleration peaks, for example about -4.8 m/s^2 while braking for more than 5 s, while experienced riders usually show short braking with milder peaks around -2 to -3 m/s^2, which matches safety guidance that very hard front braking can risk slip or rear lift [2][3][1–3][12]. Experienced riders also reach peak deceleration soon after brake onset, often within the first second, while many novices take much longer, which supports the idea of two styles, late and decisive versus early and gradual [8]. After the peak, some runs show a small bounce in acceleration before settling; the damping ratio zeta estimates how quickly that bounce fades. Many runs have very low zeta, sometimes because there is no clear bounce at all; on average experienced riders show higher values but not always, and zeta does not track strongly with other metrics, so it adds a separate view of smoothness and control. Correlations support simple trade-offs: riders who keep speed longer tend to brake for a shorter time, and those who start braking early tend to brake for longer; shorter braking windows link with sharper peaks in this sample. For practice, aim for a shorter, decisive braking phase with a moderate peak, watch time to peak and try to reach it sooner after onset without spiking too hard, and work on posture and smooth brake release to improve recovery when a bounce is present; simple overlays against an expert curve can help. Limits include a small sample, one bike and one manoeuvre in dry conditions, tuned thresholds for onset and recovery, possible phone orientation effects, a simplified damping model, and no wheel speed or brake pressure sensors, so some inferences rely only on acceleration [12].

Limitations. The sample is small and from one bike, one manoeuvre, and dry conditions. Thresholds for onset and recovery were tuned to this dataset. Phone orientation and mounting can add noise. The damping ratio assumes light, roughly linear oscillations, which is a simplification. There were no wheel speed or brake pressure sensors, so some inferences rely on acceleration only. The method is accessible and low cost, but less detailed than a fully instrumented bicycle [12].

There are several avenues to extend this research. First, increasing the sample size and diversity of riders would help validate the observed patterns statistically. It would be interesting to include intermediate skill riders or those with different types of cycling backgrounds (e.g., road cyclists vs mountain bikers) to see if the trends hold. Second, integrating additional sensors could improve insight – for instance, adding a simple wheel speed sensor could allow calculation of braking distance and exact deceleration independent of slope. Brake lever pressure sensors or gyro measurements of pitch could directly detect when the rear wheel is unloading. We also envision implementing automatic detection and feedback: with enough data, one could train a machine learning model to classify a rider as novice or experienced based on their sensor signals, or even provide real-time coaching ("brake harder now" alerts, etc.). Developing a smartphone app that guides riders through braking drills and gives immediate metrics (like our features) is a practical goal. Another extension would be to examine different maneuvers – e.g., emergency stop in a straight line, or repeated brake/turn sequences – to see if the same skill indicators apply. Lastly, exploring how braking behavior changes with training or over time would be valuable: does a novice's damping ratio and time-to-peak improve after targeted practice? Such longitudinal studies could confirm that the metrics we identified (time-to-peak, braking duration, ζ, etc.) are not just descriptive but also track progress.

5. CONCLUSION

This study demonstrated that a smartphone IMU can effectively capture and quantify braking behavior in cyclists, providing a low-cost tool for analyzing rider skill in real-world conditions. By segmenting each braking maneuver into Approach, Braking, Cornering, and Recovery phases, we extracted meaningful performance metrics that distinguish novice and experienced riders. Experienced cyclists in our tests braked later and more sharply – achieving necessary deceleration in a shorter time – and tended to recover smoothly, whereas novices braked earlier, over longer durations, and exhibited more variability and instability in their braking profiles. The introduction of a damping ratio metric offered a novel perspective on post-braking stability, highlighting how quickly a rider/bike system regains equilibrium after a hard brake. While our sample was limited, the results consistently pointed to smoother, more controlled braking among the experienced group. These findings can inform both coaching practices (by providing objective targets and visual feedback for braking technique) and educational projects (allowing students to experiment with motion data and draw insights on safety and performance). The entire data collection and analysis pipeline uses only a smartphone and basic data processing, underlining its accessibility. In urban environments where GPS alone is insufficient for detailed motion analysis[2], the phone's accelerometer proved to be a reliable anchor for timing and comparing events [7].

In summary, we have shown that even outside the laboratory, key aspects of rider braking performance can be measured and analyzed. As cycling continues to grow as both a sport and mode of transport, such accessible tools for skill assessment could contribute to safer riding. An app that logs your braking and tells you "you brake like a novice (start earlier, brake longer) or like an expert" could gamify the improvement process for enthusiasts. On the engineering side, insights from this work could inform the design of rider-assist systems (for example, smart brake lights or ABS tuning for bicycles) by understanding how humans brake in reality. Future work will aim to integrate additional sensors and algorithms to further enhance the fidelity of this analysis – for instance, incorporating brake pressure data and exploring machine learning classification of braking styles. Nonetheless, even with its current scope, our study underscores that a smartphone in your pocket can be a powerful coach: it can measure how you slow down, and in doing so, possibly help you become a faster, safer cyclist.

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