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# A normalized brake work algorithm designed to output a single metric to predict non-propulsive mountain bike performance

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ABSTRACT

*The use of a brake power meter is invaluable for describing descending performance in cycling. However, the interaction between variables such as brake work, brake time and brake power can be intricate, which might be a barrier to the utility of the brake power meter as a training tool. The aim of this study was to determine if brake power can be normalized to create a single-metric output that can capture braking performance during descents. Nine nationally competitive mountain bikers completed three trials each at race pace on a mountain bike descent using a bicycle equipped with a brake power meter. Brake power was normalized instantaneously by dividing it by the kinetic energy of the bicycle-rider system and was integrated to calculate normalized brake work (unitless). Normalized brake work (26.3 ± 15.3) was more strongly correlated ($r^2 = 0.929$; $p < 0.001$) with descending performance time (130.8 ± 20.1 s) than relative brake work (676.0 ± 152.3 J/kg; $r^2 = 0.477$; $p < 0.001$), brake time (62.3 ± 21.1; $r^2 = 0.729$; $p < 0.001$) or relative brake power (11.4 ± 2.2 W/kg; $r^2 = 0.429$; $p < 0.001$). On the descent used in this study, normalized brake work was the strongest indicator of descending performance based on braking. It is recommended that this metric be used to quickly assess brake use and provide feedback to cyclists.*

## 1. Introduction

Performance indices and predictive models in cycling sports have remained popular throughout the literature as these provide capacity for guided analyses and training interventions. To inform training, however, these indices must be valid, i.e., they must accurately separate good and poor performance (Buekers & Magill, 1995; Buekers et al., 1994; Ford et al., 2007; Ryan et al., 2002). In particular, novice learners are especially dependent on receiving valid feedback to perform correctly (Buekers et al., 1994; Ford et al., 2007). Thus, it is critical that the performance indices used to guide training are valid.

Historically, investigative models in cycling sports have focused almost exclusively on measurements of propulsive power output and propulsive work collected from on-the-bike power meters in the drivetrain (e.g., Hurst & Atkins, 2006; Macdermid et al., 2014; Miller et al., 2015; Steiner et al., 2016). Data gathered from these power meters have been able to predict the variance in cycling performance. For example, relative rates of propulsive work have a strong negative correlation with the time to complete a climb. For the practitioner and athlete, this means that to improve performance on uphill sections, competitors must aim to increase rates of relative propulsive power (W/kg). Accordingly, the intent of documented training interventions has aimed to increase relative propulsive power.

Propulsion remains an important factor for mountain bike (MTB) performance, and predictive models based on relative power output have proven useful for cross-country racing (Gregory et al., 2007; Prins et al., 2016; Vaitkevičiūtė & Milašius, 2012). However, more recent evidence has highlighted the importance of multi-dimensional performance models based on the highly variable and technical terrain ridden (Chidley et al., 2014; Miller et al., 2019; Novak et al., 2018). Indeed, while MTB ascending performance is strongly linked with relative propulsive power output, descending performance is instead linked to "skill" and not propulsive power at all. As such, a brake power meter was developed to analyze the use of brakes when mountain biking (Miller, Fink, Macdermid, Perry, & Stannard, 2018; Miller et al.

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2019). This new technology proved useful for describing non-propulsive MTB descending/turning and was also employed in conjunction with propulsive power to enhance predictive models in MTB time-trial simulations on varying terrain (Miller et al., 2019). Differences in both braking behavior and performance (i.e., time) between experienced and inexperienced riders were seen in a study of a single turn (Miller, Fink, Macdermid, Allen, & Stannard, 2018), raising the possibility that the inexperienced riders could improve performance by adopting braking patterns more like the experienced riders. There is, however, a need to extend the use of the brake power meter from a single turn, in highly controlled conditions, to a more ecologically valid situation, i.e. a technical descent with turns of different radii and with differences in the approach speed to the turn.

To date, this new brake power meter technology has focused on utilizing the same kinds of variables collected from propulsive power meters – such as power and work – due to their relative relevance, non-complexity and prevalence of use (Miller et al., 2017; Miller, Fink, Macdermid, Perry, & Stannard, 2018; Miller et al., 2019). The measurement of brake work and power is similar to the measurement of propulsive power and work; however, the magnitude of braking necessary to slow riders depends on a number of variables, which complicates the interaction between the brake work and brake power performed and how these affect the speed of the bike. These variables were significantly correlated with performance (i.e., time), but neither variable explained a high percentage of the variance in performance time ($r^2 < .500$, less than the correlation for the time spent braking) (Miller et al., 2019), which may be a barrier to the effectiveness of brake training interventions and descending performance explanation when using a brake power meter.

To highlight some of the complexities of brake power meter data analysis, simple energy equations can be utilized to compare braking data and effects on performance given the law of conservation of energy. At the same time, these same equations may also help to reduce brake power meter data to more usable and comparable metrics. A brief sequence of the braking variables collected and the physical comparisons made are outlined below.

Brake power (W) is calculated as the product of brake torque and the velocity of the bike (Eq. 1):

$$PB = \omega_f (\tau_f + \tau_r)$$

where $PB$ is brake power, $\omega_f$ is the angular velocity of the front wheel, and $\tau_f$ and $\tau_r$ are the brake torque at the front and rear wheels, respectively (Miller et al., 2019).

Brake work ($WB$, in J) is calculated by integrating the product of front and rear brake power (Eq. 2):

$$WB = \int_0^t (PBf + PBr)dt$$

The brake work completed by a rider slowing down on flat ground is equal to the change in kinetic energy when accounting for drag and rolling resistance (Eq. 3):

$$WB + E_{rr} + E_d = \Delta E_K$$

where, $E_{rr}$ is rolling resistance, $E_d$ is energy lost to aerodynamic drag, and $\Delta E_K$ is the change in kinetic energy as explained previously (Miller et al., 2017).

The change in kinetic energy of the bicycle-rider system can be explained given (Eq. 4):

$$\Delta E_K = \left[\left(\tfrac{1}{2}mv_2^2\right) - \left(\tfrac{1}{2}mv_1^2\right)\right] + \left[\left(\tfrac{1}{2}\mathrm{I}\omega_2^2\right) - \left(\tfrac{1}{2}\mathrm{I}\omega_1^2\right)\right]$$

where $m$ is the combined mass of the bike and the rider wearing cycling gear, $v$ is the velocity, I is the moment of inertia, and $\omega$ is the angular velocity of the front wheel.

The instantaneous kinetic energy can therefore be calculated as (Eq. 5):

$$E_K = \left(\tfrac{1}{2}mv^2\right) + \left(\tfrac{1}{2}\mathrm{I}\omega^2\right)$$

where $v$ and $\omega$ are instantaneous velocity and angular velocity, respectively.

In Eq. 5, $m$ and $v$ are important to note. Assuming two riders of different mass, the kinetic energy at any given time is not equal, and thus the brake work required to slow these two masses will not be equal. More importantly, two riders of the same mass but travelling at different velocities will have different kinetic energy because the kinetic energy of each rider is proportional to velocity squared. For example, a rider traveling twice as fast will require four times the brake work to come to a complete stop. Indeed, with differences in the amount of brake work required, the brake power recorded will be different in these cases—even with the same time spent braking. Although we understand that it is important to complete brake work across a very short brake time to minimize the time spent traveling slowly – and that this leads to a very high brake power – it is difficult to make comparisons between individuals even when accounting for mass. Accordingly, it is understandable why traditional measurements of brake work or average brake power have a relatively weak relationship with performance time across a given distance. This potential barrier to the understanding and comparison of the data must be overcome for brake power meter measurements to have utility for training.

Given the complexities in analyzing brake data, it is sensible to develop an algorithm that can calculate the amount of braking done by the rider in relation to both the total mass and the velocity of the bicycle-rider system. One way to do this could be to divide the instantaneous brake power by the kinetic energy of the bicycle-rider system, resulting in a variable with units of (1/s). This normalization of brake power effectively adjusts the braking power based on both mass and velocity. Then, normalized brake power can be integrated to find normalized brake work, which is a unitless measure. Since MTB descending performance is likely linked to braking and cannot be predicted using propulsive models, a normalized brake work model would help to describe and analyze these performances.

To provide better feedback to cyclists, the aim of this study is to determine what variables correlate most strongly with performance during a mountain biking descent under ecologically valid conditions. It is hypothesized that variations in performance time on a mountain bike descending track could be better explained by a new normalized brake work than by traditional brake metrics of relative brake work, brake time, or relative brake power, henceforth signifying the practical relevance of the algorithm in question.

## 2. Methods

### *2.1 Participants and Task*

Nine nationally competitive mountain bikers (mean ± SD: age = 25.6 ± 3.6 years; body mass = 77.4 ±11.6 kg; height = 177.2 ± 11.2 cm) volunteered to take part in this study. Riders were asked to ride as quickly as possible on a track (Figure 1) that was chosen because of the descending nature which eliminated performance benefits due to pedaling (Miller, Macdermid, Fink, & Stannard, 2017). Participants completed three consecutive trials with 15 min epoch between. All participants were familiar with the track having previously ridden it on their own time. Informed consent was obtained prior to testing, and the methods used for testing were approved by Massey University's Human Ethics Committee.

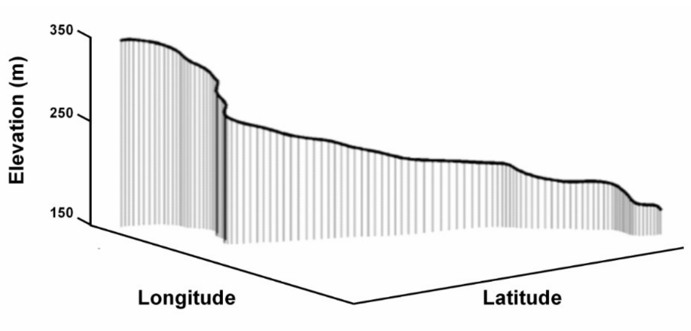


Figure 1: Elevation profile of the descending track used for testing in this study. The total distance was 1.01 km with a total elevation loss of 165 m (average gradient of -16.3%). This track was chosen based in its previous use which indicated that performance time was not dependent on propulsive work.

### *2.2 Apparatus*

Prior to each test session, each participant was weighed while wearing cycling apparel, which included clothing, helmet and shoes. Participants all rode the same mountain bike (Trance 1, Giant Bicycles, New Zealand), which had suspension adjusted to manufacturer specifications pre-testing and had tires inflated to a standardized pressure (Macdermid et al., 2015). The bike was outfitted with a custom designed brake power meter (detailed in Miller, Fink, Macdermid, Perry, & Stannard, 2018) that continuously sampled and recorded at 128 Hz, and a propulsive power meter (S2275, Quarq, Spearfish, SD, USA) that recorded data at 1 Hz. Both the propulsive and brake power meters were calibrated prior to each test session, the Quarq by manually zeroed according to manufacturer specifications using a Garmin 510 (Garmin, Olathe, Kansas, USA) and the brake power meter by hanging known weights from the rim and recording the torque observed by the sensor. Using this method of calibrating the brake power meter, the brake power meter has been shown accurate to within 2% on the road and 5% on a dirt path (Miller, Fink, Macdermid, Perry, & Stannard, 2018). Brake power meter data were recorded on a stand-alone data logger (DATAQ UHS710; DATAQ Instruments, Akron Ohio, USA) attached to the bicycle handlebars while propulsive power was recorded on a portable cycle computer (510; Garmin Ltd., Schaffhausen, Switzerland). The total mass of the bicycle and all equipment was 18.64 kg; this is considerably heavier than a typical competition mountain bike, owing to the relatively large mass of the prototype brake power meter.

### *2.3 Procedure and Analysis*

Brake power meter data was analyzed using Matlab R2011b (The MathWorks, Inc., Natick, MA, USA) to calculate variables of interest. Distance travelled during each trial was calculated by integrating the angular velocity of the front wheel over the descent and multiplying by the radius of the wheel plus tire. Performance time (s) was estimated as the time at which the distance travelled was equal to the distance of the track. There is a potential issue in that it assumes a given distance for the descent, which is not correct given that different paths on the track would result in different distances, but this method was chosen because it could be calculated without relying on GPS, which could not be accurately synced with the brake power meter. Brake power and brake work were calculated as explained in Eq. 1 and 2. Relative brake work was calculated by dividing the brake work over the entire descent by the mass of the rider plus bicycle. Any measurement that did not exceed 8 Nm was removed from analysis to reduce the effect of noise. Brake time (s) was the total time that either brake exceeded 8 Nm. Relative brake power (W/kg) was calculated as the product of relative brake work divided by brake time.

Normalized brake power (NBP), is brake power adjusted for kinetic energy, and was calculated instantaneously as (Eq. 6):

$$\mathrm{NBP} = \frac{\omega_f(\tau_f + \tau_r)}{\left(\frac{1}{2}mv^2\right) + \left(\frac{1}{2}\mathrm{I}\omega^2\right)}$$

where $\omega_f$ is the angular velocity of the front wheel, and $\tau_f$ and $\tau_r$ are the brake torque at the front and rear wheels respectively, *m* is the mass of the rider plus bicycle, I is the moment of inertia of the wheels, *v* is the instantaneous velocity, and ω is the instantaneous angular velocity of the wheels. The units for normalized brake power are 1/s.

Normalized brake power was integrated to calculate normalized brake work (NBW) across the descent (Eq. 7):

$$\mathrm{NBW} = \int_0^t \mathrm{NBP}dt$$

where normalized brake work is unitless.

As an additional method to visualize the data, histograms of normalized brake power were created by creating 10 bins, separated by 0.05 1/s. Values below 0.05 1/s were removed from the analysis, since these were extremely light braking events, while values above 0.50 1/s were included in the same bin due to their infrequent occurrence.

### 2.4 Statistical Approach

All trials for all participants were included in the analysis All statistical analyses were completed in GraphPad Prism 7.00 (GraphPad Software, San Diego California, USA). The mean ± standard deviation (SD) was calculated for performance time, relative brake work (brake work divided by the mass of the bicycle and rider), brake time, relative brake power (brake power divided by the mass of the bicycle and rider) and normalized brake work across all trials. The relationship between each of the variables and performance time was determined by applying a mixed model regression, with the y-intercept being a random factor. The fitted slope and y-intercept were used to calculate the degree of relationship between observed and fitted data for each of the variables. First, the overall sum of squares was calculated:

$$SSTO = \sum (Y_i - \bar{Y})^2$$

where Y is the variable of interest and $\bar{Y}$ is the mean of that variable. The error sum of squares was calculated using the fitted slope and y-intercept:

$$SSE = \sum \left(Y_i - \hat{Y}\right)^2$$

where $\hat{Y}$ is the fitted value. R2 was then calculated using

$$R^2 = 1 - \left(\frac{SSE}{SSTO}\right)$$

This calculation was performed for all variables to quantify the relationship between the variables of interest, coefficients of determination were also calculated between normalized brake power and relative brake work, brake time, and relative brake work. The alpha value for all tests was set to 0.05.

## 3. Results

The potential energy at the onset of the descent was 154,578 ±18,887 J, and participants completed an average propulsive work equating to 1,231 ± 3,217 J. Descriptive data for performance and braking variables are highlighted in Table 1. The relationship between performance time and relative brake work, brake time, relative brake power and normalized brake work, respectively, are reported in Figure 2A-D. Normalized brake work on the track used in this study displayed the strongest relationship with performance time ($r^2 = 0.912$, $p < 0.001$). Normalized brake work was also significantly correlated to measurements of relative brake work ($r^2 = 0.669$, $p < 0.001$), brake time ($r^2 = 0.7999$, $p < 0.001$), and relative brake power ($r^2 = 0.293$, $p = 0.0036$).

Table 1. Mean ± SD for performance and braking variables

| Variable | Mean | SD |
|---|---|---|
| Performance time (s) | 130.8 | 20.1 |
| Velocity (km/h) | 28.4 | 3.8 |
| Relative brake work (J/kg) | 676.0 | 152.3 |
| Brake time (s) | 62.3 | 21.1 |
| Relative brake power (W/kg) | 11.4 | 2.2 |
| Normalized brake work | 26.3 | 15.3 |

Note. Values were obtained from 27 descending trials on a mountain bike track that was not dependent on propulsive work

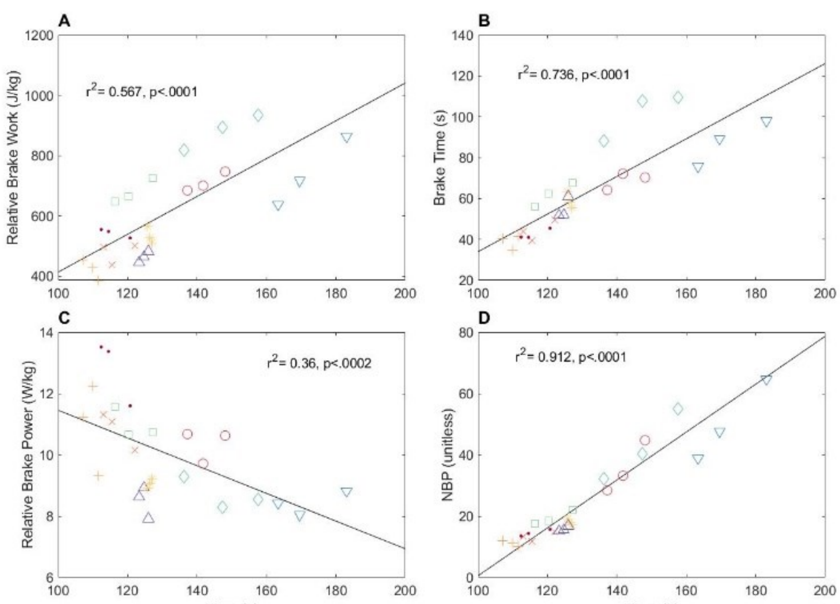


Figure 2: The relationship between performance time (s) on the mountain bike descent and A) relative brake work (J/kg); B) brake time (s); C) relative brake power (W/kg); and D) normalized brake work. The symbols and colors represent different riders.

To illustrate differences between skill levels, one trial was selected each from a high-performer (performance time = 115.4 s; normalized brake work = 13.1; relative brake work = 529.1 J/kg) while another was selected as that of a low-performer (performance time = 169.9 s; normalized brake work = 43.0; relative brake work = 966.5 J/kg). The relative brake power and normalized brake power from a small section of these trials are highlighted in Figure 3, which was chosen due to clear visual differences for each of comparison. From each entire trial, a histogram was created to indicate the magnitude of normalized brake power as a percent of brake time (Figure 4). What can be seen from these figures is that the high-performer was generating less normalized brake power during the same section of the descent (Figure 3). Moreover, when looking across the entire descent (Figure 4), the low performing rider spent a greater percentage of the braking time with high normalized brake powers.

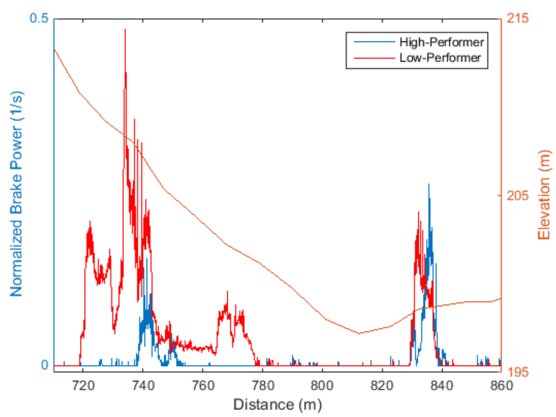


Figure 3: Graphical representation of normalized brake power (1/s) across a 150 m portion of the descent from one trial each by a high-performing and low-performing mountain biker. The normalized brake work was 0.13 and 0.80 for the high-performer and low-performer, respectively. The time to complete this section was 14.72 and 18.22 s for the high- and low-performer, respectively, which equated to 10.91 and 8.23 m/s, respectively.

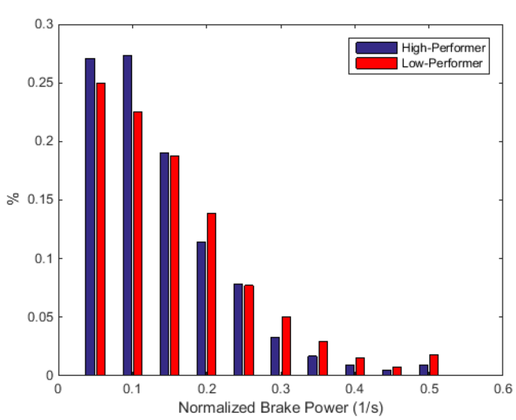


Figure 4: Frequency distribution of normalized brake power (1/s) comparing a high- and low-performing mountain biker.

## 4. Discussion

Braking has been identified as an important factor for performance in mountain biking; however, the exact relationship between braking and performance is difficult to confirm (e.g., Miller, Fink, Macdermid, Allen, & Stannard, 2018; Miller et al., 2019). This is the first investigation to utilize an algorithm to normalize brake power as a proportion of the kinetic energy of the bicycle-rider system, effectively scaling rider input to the brakes to both mass and velocity. It was hypothesized that normalized brake work would be more strongly associated with descending performance than traditional brake power meter metrics. Although relative brake work, brake time and relative brake power were all significantly associated with performance time on a mountain bike descending track (Figure 2A-C), normalized brake work explained more variance in descending performance time on the track used in this study (Figure 2D). By itself this result is important, as it indicates that normalized brake work could be used to quantify the contribution of skill to descending, and thus could be used to provide feedback about skill; this metric would be particularly useful in situations where the downhill, by its nature, requires significant propulsive work (unlike the downhill tested here).

Eq. 1-3 highlighted some of the complexities when utilizing traditional brake metrics such as relative brake work and relative brake power to explain variations in MTB descending time. The present method for calculating normalized brake power (Eq. 6) normalizes instantaneous brake power based on mass and velocity and is indicative of the proportion of kinetic energy removed at any time during braking. Once normalized brake power is integrated over time (Eq. 7), the resultant normalized brake work metric theoretically offers a broader representation of the conservation of kinetic energy with respect to braking than traditional brake measures. Since the potential energy of the bicycle-rider system is a product of the mass of the system times the height of the track and gravity, and there was negligible propulsive work completed by participants, the normalized brake work algorithm has sound theory for use in explaining the present descending performances.

The results presented in this study firstly reinforce the relationship between braking and mountain bike descending performance (Figure 2A-C). Indeed, the fastest performance times were associated with reduced relative brake work, reduced brake time, and increased relative brake power. These findings are not surprising, but support the qualitative importance of efficiently controlling the speed of the bicycle down the hill (Chidley et al., 2014; Hurst & Atkins, 2006) and reinforce earlier braking investigations (Miller et al., 2017; Miller, Fink, Macdermid, Allen, & Stannard, 2018; Miller et al., 2019). However, the main finding presently is that the normalized brake work metric was more strongly related to performance (Figure 2D) and can therefore explain more variation in descending performance than traditional measures from a brake power meter considered in isolation. This finding is promising because normalized brake work can indeed explain the variation in descending performance based on brake power meter data alone, thus eliminating the need for qualitative measures of descending performance or for other equipment. Moreover, the single metric output reduces the complexity of multivariate analyses of braking performance, which eliminates a potential barrier to use of the brake power meter for skill improvement.

Finding the most appropriate variable to provide feedback to riders is complicated by the correlations between normalized brake work and other braking variables measured in the study (e.g. brake time, relative brake work) as well as, potentially, braking variables not measured in the study (e.g., location of the braking events). One factor affecting performance is the location of the braking, which has been previously identified as a major difference between experienced and inexperienced riders (Miller, Fink, Macdermid, Allen, & Stannard, 2018). This factor that could likely benefit from visual inspection and should be explored further. Another braking factor affecting descending performance in the shape of the braking curve, as can be seen in Figure 3. A late-braking strategy is displayed by the high-performing rider, and acts to reduce performance time since a greater proportion of the time is spent moving more quickly. While the shape of the braking curve may indeed affect performance, the shape cannot be understood solely by looking at normalized brake work and may likely rely on visual inspection. Similarly, line choice likely factors into performance differences as well. Firstly, these could be analyzed based on GPS position, though these devices lack some resolution (Coutts et al., 2010). Furthermore, it is likely that there is an interaction with other elements of skill, particularly with the path chosen to go around corners, that will affect braking. For example, by changing the path going around a corner, the radius of the turn, and therefore the centripetal force required to make the turn at a given velocity, will change. Thus, changes in path (or line around a corner) will likely play a role in determining how much braking is necessary for the corner, which will in turn be reflected in the braking metrics. These complications are acknowledged, and future research will have to explore these relationships in greater detail. Nevertheless, even with these limitations, normalized brake power is useful as a way of quantifying aspects of skill related to the control of velocity during descents.

Because the study of braking in mountain biking is a relatively recent subject of study, at present we can only give suggestions for how normalized brake power could be used: research along these lines is continuing. One thing that is clear is that what constitutes a good normalized brake power will depend on the course that is being ridden: a straight line gentle descent will require little, if any, braking and therefore a normalized brake power of close to 0 for riders of any skill level; a very technical descent, requiring many sharp turns, on the other hand, will require a larger normalized brake power for even the most skilled rider. For this reason, it is recommended that comparisons only be made between descents of the same trail. By adjusting brake power for both mass and velocity, however, comparisons between individuals can be made, and also within the same individual between different runs (e.g., Miller, Fink, Macdermid, Allen, & Stannard, 2018; Miller et al., 2019, although these studies predated the normalized brake power).

Normalized brake work can also be used for entire descents, but could also be broken down for individual braking events. By calculating a normalized brake work for each corner or each braking event, and comparing the normalized brake work for each braking event to either other riders, or to the rider's previous descents, normalized brake work could be used to identify potential problem areas on the course. For example, Figure 3 shows a high performing (blue) and low performing (red) rider on the same section of the course. This section contains two turns, and therefore two braking events. There was little difference between the two riders on the second braking event, suggesting that braking event was not a problem for the low-performing rider on that turn. On the first braking event, however, there were large differences between the two, which would indicate the low performing rider could improve performance by concentrating on that particular braking event or turn. That information, by itself, could be useful but when combined with GPS or video, the exact nature of the problem (e.g. incorrect line leading into the turn, requiring more braking, braking past the apex of the turn, etc.) could be explored in more detail.

Development of a brake power meter, and identification of relevant metrics to describe braking, also raises the possibility for studies of the visual (and potentially other perceptual) information used to guide braking. Control of braking has been studied using an ecological framework (e.g. Fajen, 2005; Fajen, 2008; Lee, 1976; Yilmaz & Warren, 1995), but these studies have examined the case where the person is coming to a complete stop. In mountain biking, the goal is to move around a corner as quickly as possible, and only rarely coming to a complete stop. Because the goal is different, the proposed models do not apply, and the tau-based control (e.g. Lee, 1976; Yilmaz & Warren, 1995) must be modified. Given the nature of the task, it seems likely that the affordances involved must be directly incorporated in the control laws governing braking (e.g., Fajen, 2007). At present, no existing models for the control of braking appear to be sufficient for explaining the control of braking in mountain biking, but this is an area that could be further explored.

This study shows that the normalized brake work algorithm has sound theoretical reasoning for use in comparing brake data between riders travelling at different speeds. Normalized brake work can describe more variation in descending performance than other braking measures, which gives the brake power meter greater utility as a training tool. It is recommended that training interventions be utilized to enhance the braking patterns of low-performing mountain bikers, which should come as a benefit to their normalized brake work.

## Conflict of Interest

Matthew Miller and Philip Fink are co-inventors of the brake power meter and are actively involved in commercializing the device.

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