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# Pacing Variability and Performance in a 100 Mile Ultra Marathon

Brendan Gilpatrick
*University of Maine*, brendan.gilpatrick@maine.edu

**PACING VARIABILITY AND PERFORMANCE IN A 100 MILE ULTRA MARATHON**

By

Brendan Gilpatrick

A THESIS

Submitted in Partial Fulfillment of the

Requirements for the Degree of

Master of Science

(in Kinesiology and Physical Education)

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Advisory Committee:

Robert Lehnhard, Director of School of KPEAT, Advisor

Christopher J. Nightingale, Professor of Physical Education and Athletic Training

Sid Mitchell, Associate Professor of Education

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The purpose of this research was to explore the relationship between pacing variability and performance during a 100 mile trail race with significant changes in elevation. Changes in pace throughout an endurance event of this length could lead to insight into the relationship of early pacing on overall performance and placing among finishers. Due to variables like changes in terrain or weather it could prove difficult to construct a way to analyze data from these races. Race data from a loop style course with significant elevation change was used to determine if 1). There were significant changes in pace per lap among those that finished and 2). Whether there is a relationship between pacing variance and overall finishing place. Finishers were broken down into three groups: Group 1 ($1^{st}$-$21^{st}$), Group 2 ($22^{nd}$ – $42^{nd}$), and Group 3 ($43^{rd}$ – $63^{rd}$). After statistical analysis it was concluded that while all runners demonstrated positive pacing over the course of the race that runners in Group 1 demonstrated less pacing variance than the slower groups (Group 2 and 3) and finished higher in the overall standings when compared to runners with greater pacing variance.

## ACKNOWLEDGEMENTS

Many thanks go out to my thesis committee, Dr. Lehnhard, Dr. Nightingale, and Dr. Sid Mitchell. Their support and feedback throughout this process has been critical to the completion of this project. I would also like to thank my wife Jessica for both her patience and constant support while pursing my graduate degree at the University of Maine.

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**PACING VARIABILITY AND PERFORMANCE IN 100 MILE ULTRA MARATHONS**

As ultramarathons have become more popular and runners push performances over varying courses and terrain, it is important to start looking at pacing variation in these events as they could offer insight into creating strategies that could lead to improved finishing rates as well as faster finishing times. There has been research done on pacing variability for up to 100km races, but this was done on a flat loop style course with little variation in elevation change. A 100-mile race is 38% longer in distance and a more popular race distance.

Little research has looked at pacing variance in a 100-mile race that traverses mountainous terrain. Due to variables like changes in terrain or weather it could prove difficult to construct a way to analyze data from these races. However, by utilizing race data of a loop style course, pacing variability could be examined to determine if 1). There were significant changes in pace per lap among those that finished versus those that did not and 2). Whether there is a relationship between variation and overall finishing place.

**Current Literature**

Several studies have looked at individual races and differences between pacing of elite runners versus the remaining field of athletes in 100-kilometer races (Lambert et al., 2004; see also Renfree, 2016; Rust et al., 2015). This research has focused on the influence of performance level, age, and gender on pacing strategy during 100-km ultramarathons. Female runners showed slower starting speeds than male runners and faster finishing speeds. When comparing multiple years from the same race it was concluded runners in the 18-24 year old age group were slower than runners in most other age groups and that there was no trend of older runners slowing down during the race, potentially demonstrating the significance of race experience and a pacing strategy may have (Rüst et al., 2015).

**Physiological Limitations**

There are several theories that relate to how fatigue and physical exertion is regulated that prove beneficial when considering pacing variability and pacing selection. The central governor is theorized to be a mechanism of the central nervous system where the input of information of metabolic needs, current physiological states, and various motivational drives regulate physical exertion to save the organism from catastrophic homeostatic failures during physical exertion (Noakes et al., 2005). Meaning that all changes in pace during exercise including stopping altogether occurs as part of a regulatory system that is continuously adjusting pace to protect the body from damage. This regulatory system is functioning subconsciously and is osculating helping to ensure homeostasis with feedback from the central nervous system as well as metabolic feedback and other changes in peripheral organs. For the runner this means that the brain is pacing the body to ensure that the preplanned activity can be completed without doing harm to cellular homeostasis (Noakes et al., 2005).

A more complete model is one where self-regulatory fatigue informs central governor theory, including elements such as current workload, anticipated future exertion, previous experiences, opportunity costs, and motivation. This would mean a more dynamic mechanism is in place governing current output and remaining energy reserves and weighing them against remaining work and goal importance. These would then influence subjective fatigue and willingness of task completion (Evans, et al., 2016). This aligns closer to the Integrative Governor theory which suggests both psychological and physiological drives are linked to homeostasis and regulation (St Clair Gibson, et al., 2018 & McMorris et al., 2018). Governing mechanisms such as these are critical when considering how and why a runner's pace selection varies for an endurance event that is 100 miles in length and will take up to 36 hours to complete.

Physiological changes that may happen during a race should also be a considering factor when analyzing pacing and performance. There has been research on the biological and neuromuscular changes that occur during mountain ultramarathons. This includes research done during the Tor de Geants, a 200 mile race through the Italian alps that can take runners 4 to 5 days to complete. When they compared their results to UTMB, a race half the distance, they found that neuromuscular fatigue was generally less altered and muscle damage and inflammation was significantly lower (Saugy et al., 2013). This is most likely due to runners in this longer event employing a more conservative pacing strategy from the start of the race and with that lower intensity from the beginning neuromuscular function is preserved.

**Defining Pacing Variance and Significance**

Runners competing across all distances employ strategies around pacing that factor in multiple variables (distance, elevation loss/gain, weather, competition, past performances, current fitness, etc.) Change in velocity has been examined in shorter distance races including the 5000m and 10000m world record races where the first and last kilometers were significantly faster than the middle portion of the race resulting in overall even pacing with an end acceleration portion (Tucker et al., 2006). The goal among ultramarathon runners is to reduce pacing variance, as even pacing has been shown to be associated with faster finishing times (Suter et al., 2020). However, positive pacing, where a runner's pace slows over the course of the race, has been observed in events that are greater than marathon where speed decreases over the event as it has been observed in recreational runners (Angus and Waterhouse, 2011 & Lambert et al., 2004). What their analysis showed was that slower runners demonstrated a greater decrease in their mean running speed and runners were unable to maintain their starting pace. Faster runners ran with less variance in pacing, started the race faster than the slower runners and were able to maintain initial starting speed longer before slowing down. Similarly, when the race distance increased to 173km over hilly terrain there was a decrease in speed in all participants as the distance completed overall performance was not correlated to expected predictors of overall running performance (variability of speed, speed loss), or to the total time stopped where the runner was not advancing on the course due to time spent at aid stations (Kerhervé et al., 2016).

Pacing variance has been looked at in timed events (6-hour and 24-hours) as well where the objective is to complete the most amount of mileage in the allotted time. While the goal of these events is to accumulate the greatest distance in the given amount of time, they demonstrate the importance of reducing pacing variance during an endurance event to achieve a better performance while reducing overall perceived effort and fatigue. During a 24-hour format race it was determined that the faster runners started at a relatively lower effort and adopted a more even pacing strategy than slower runners When runners were grouped by finishing distance/placement faster runners ran at a relatively faster speed over the 2$^{nd}$ half of the course when compared to slower runners on the 2$^{nd}$ half of the course suggesting that success for the faster runners was achieved with less pacing variance (Takayama et al., 2016). These findings were confirmed in additional research focused on the 24 hour race determining that there were significant differences in mean running speeds among performance groups. Faster runners (Group 1) displayed a more even pacing strategy than their slower competitors including a more conservative initial speed (mainly in the first 3 hours), slowing down less as the race progressed. Slower runners (Groups 2–4) were unable to maintain their initial speed as much as the fastest runners, reducing their speed more quickly, as well as displaying the greatest speed fluctuations throughout the race mist significantly in the final hour of the race (Bossi, 2017).

## METHODS

The Hurt 100 Miler is held on the island of Oahu. It is conducted on trails within the jurisdiction of the State of Hawaiʻi Department of Land and Natural Resources (DLNR), Division of Forestry and Wildlife, Nā Ala Hele program. The HURT 100 course consists almost exclusively of technical, single-track trail on surfaces that include roots, rocks, and soil in a wide range of conditions. Over the 100-mile course, the elevation ranges from 300 to 1900 feet above sea level. The total cumulative elevation gain is roughly 24,500 feet. There are a total of twenty stream crossings. Mānoa Stream and Nuʻuanu Stream are each crossed twice per lap at locations close to the Paradise Park and Nu'uanu Aid Stations. There are 3 aid stations on the 20 mile course where runners' splits are recorded: Makiki 0.0/20 miles (start/finish), Manoa (7.3 miles), and Nuuanu (12.8 miles) (hurt100.com, 2021).

The dataset for this study was obtained from the website Ultrasignup.com who hosts results and runners' splits reported by the race and is publicly available information. Results from the 2020 race were used for this analysis. The high temperature on the island of Oahu on January 18, 2020 was 81°F with a low of 70°F with an average wind speed of 10.5mph and 55.5% humidity throughout the day. As this race has a 36 hour cutoff for finishing, the weather was similar on the 2$^{nd}$ day of the race with the high of 81°F with a low of 72°F and average wind speed of 11.25mph with an average humidity of 55.5%. There was little to no precipitation in the days leading up to the 2020 race which led to relatively dry footing conditions. This was a critical factor in selecting what year of data to use as a wet course could affect the footing of each runner and have a significant impact on pacing due to perceived risk by each athlete as they navigated the course. In 2020 there were 125 runners that started the race, made up of 39 female runners and 86 male runners. There were 63 total finishers out of the 125 starters. Lap data from the 62 runners who did not finish the race was excluded from the analysis as the intended goal of finishing was not met.

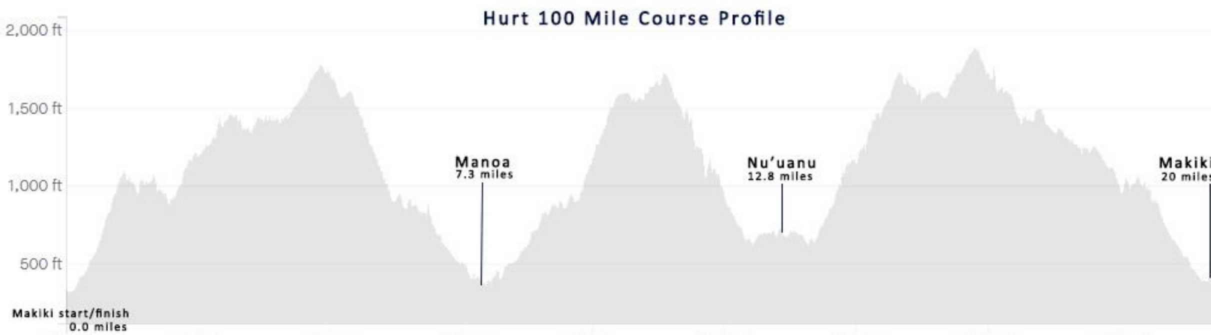



**Figure 1. Elevation profile of the Hurt 100 Mile course**

**Statistical Analysis**

The time periods between the five laps for the three "check-in" spots (Manoa, Nuuanu, and Makiki) were calculated. There was a total of four (4) time periods calculated for Manoa, Nuuanu, and Makiki: time between Lap 1 and Lap 2 (1-2), time between Lap 2 and Lap 3 (2-3), time between Lap 3 and Lap 4 (3-4), and time between Lap 4 and Lap 5 (4-5). The time periods in between laps were then compared using a within-subjects repeated-measures ANOVA. The statistical assumptions of normality and sphericity were checked before interpreting the ANOVA analyses.

A Greenhouse-Geisser correction was applied when a violation of sphericity occurred. When a significant main effect was detected, post hoc testing was performed to test for pairwise differences amongst the laps. Means and standard deviations were reported for the ANOVA analyses. To compare the variability of pace according to where participants placed in the competition, the $n = 63$ runners were put into three independent groups according to where they finished (Group 1 = $1^{st}$-$21^{st}$, Group 2 = $22^{nd}$ – $42^{nd}$, Group 3 = $43^{rd}$ – $63^{rd}$) and each group respective pace across the laps was compared using a mixed-effects ANOVA. The statistical assumptions of normality, homogeneity of variance, sphericity, and homogeneity of covariance were checked before interpretation of the analyses. Significant interactions between group and pace were further explored with post hoc testing. Marginal means with 95% confidence intervals were reported and interpreted. All statistical analyses were conducted using SPSS Version 26 (Armonk, NY: IBM Corp.) and statistical significance was noted at a *p*-value of 0.05.

**Statistical Results**

For the time periods associated with Manoa, a statistically significant main effect was detected, $F(3, 183) = 247.54$, $p < 0.001$, partial eta squared = 0.80, power = 1.00. Post hoc testing determined that there were statistically significant increases in lap time in between laps 1-2 and laps 2-3, laps 1-2 and laps 3-4, laps 1-2 and laps 4-5, laps 2-3 and laps 3-4, laps 2-3 and laps 3-4, $p < 0.001$, as well as between laps 3-4 and 4-5, $p = 0.002$. For the Nuuanu analysis, a significant main effect was detected, $F(3, 186) = 194.85$, $p < 0.001$, partial eta squared = 0.76, power = 1.00. The subsequent post hoc testing found statistically significant increases in time between laps 1-2 and laps 2-3, laps 1-2 and laps 3-4, laps 1-2 and laps 4-5, laps 2-3 and laps 3-4, laps 2-3 and laps 3-4, $p < 0.001$, but not between laps 3-4 and laps 4-5, $p = 0.922$. Finally, for the Makiki analysis, a significant main effect was detected, $F(3,186) = 129.36$, $p < 0.001$, partial eta squared = 0.68, power = 1.00. Further post hoc testing showed significant increases in time between laps 1-2 and laps 2-3, laps 1-2 and laps 3-4, laps 1-2 and laps 4-5, laps 2-3 and laps 3-4, laps 2-3 and laps 3-4, $p < 0.001$, and then a significant decrease in time between laps 3-4 and laps 4-5, $p = 0.02$. The means and standard deviations for the three ANOVA analyses can be found in Table 1. Figure 2, 3, and 4 present the findings of the ANOVA analyses graphically for Manoa, Nuuanu, and Makiki.

For the mixed-effects ANOVA focused on Manoa, a significant interaction effect was detected, $F(6,177) = 8.67$, $p < 0.001$, partial eta squared = 0.23, power = 1.00. Post hoc testing showed significant differences for the majority of comparisons, with the exception of Group 2 and Group 3 for 4-5 time period, $p = 0.85$. All post hoc tests for Manoa are presented in Table 2 and visually in Figure 5. A significant interaction was detected for Nuuanu as well, $F(6,180) = 7.88$, $p < 0.001$, partial eta squared = 0.21, power = 0.99. Statistical significance was found in a post hoc fashion, with exception of the 3-4 time period between Groups 2 and 3, $p = 0.06$, and in the 4-5 time period between Groups 2 and 3, $p = 0.99$. See Table 3 and Figure 6 for the descriptive statistics related to the interaction in Nuuanu. Finally, a significant interaction effect was detected between the rank Groups and time periods, $F(6,180) = 3.12$, $p = 0.01$, partial eta squared = 0.09, power = 0.83. Post hoc testing showed significant differences for all comparisons, except for in the 3-4 period between Groups 2 and 3, $p = 0.40$, and the 4-5 period between Groups 2 and 3, $p = 0.14$. See Table 4 and Figure 7 for the relevant statistics for the interaction associated with Makiki.

**Table 1. Time Differences between Laps at Manoa, Nuuanu, and Makiki in minutes**

| Segment | Time Period | Mean (SD) | *p*-value |
|---|---|---|---|
| Manoa | | *minutes* | |
| | Lap 1 and Lap 2 | 315.18 (38.56) | |
| | Lap 2 and Lap 3 | 363.20 (49.25) | |
| | Lap 3 and Lap 4 | 419.40 (64.37) | |
| | Lap 4 and Lap 5 | 436.64 (53.99) | < 0.001 |
| Nuuanu | | | |
| | Lap 1 and Lap 2 | 329.58 (40.51) | |
| | Lap 2 and Lap 3 | 377.96 (53.05) | |
| | Lap 3 and Lap 4 | 432.31 (66.28) | |
| | Lap 4 and Lap 5 | 432.86 (48.60) | < 0.001 |
| Makiki | | | |
| | Lap 1 and Lap 2 | 343.70 (43.69) | |
| | Lap 2 and Lap 3 | 399.52 (59.20) | |
| | Lap 3 and Lap 4 | 439.70 (63.64) | |
| | Lap 4 and Lap 5 | 425.90 (52.10) | < 0.001 |

**Table 2. Post Hoc Tests for Significant Interaction – Manoa**

| Time Period | Placement Group Reference | Placement Group | Mean Difference (95% CI) | *p*-value |
|---|---|---|---|---|
| 1-2 | 1st-21st | 22nd-42nd | -37.64 (-52.60 - -22.69) | < 0.001 |
| | | 43rd-63rd | -73.64 (-88.41 - -58.86) | < 0.001 |
| | 22nd-42nd | 43-63rd | -35.99 (-50.95 - -21.04) | < 0.001 |
| 2-3 | 1st-21st | 22nd-42nd | -63.51 (-79.93 - -47.08) | < 0.001 |
| | | 43rd-63rd | -99.87 (-116.09 - -83.65) | < 0.001 |
| | 22nd-42nd | 43-63rd | -36.37 ( -52.79 - -19.94) | < 0.001 |
| 3-4 | 1st-21st | 22nd-42nd | -98.86 (-120.62 - -77.09) | < 0.001 |
| | | 43rd-63rd | -124.66 (-146.16 - -103.17) | < 0.001 |
| | 22nd-42nd | 43-63rd | -25.81 (-47.57 - -4.05) | 0.021 |
| 4-5 | 1st-21st | 22nd-42nd | -85.57 (-108.40 - -62.75) | < 0.001 |
| | | 43rd-63rd | -83.43 (-105.98 - -60.89) | < 0.001 |
| | 22nd-42nd | 43-63rd | -2.14 (-24.96 - -20.69) | 0.85 |

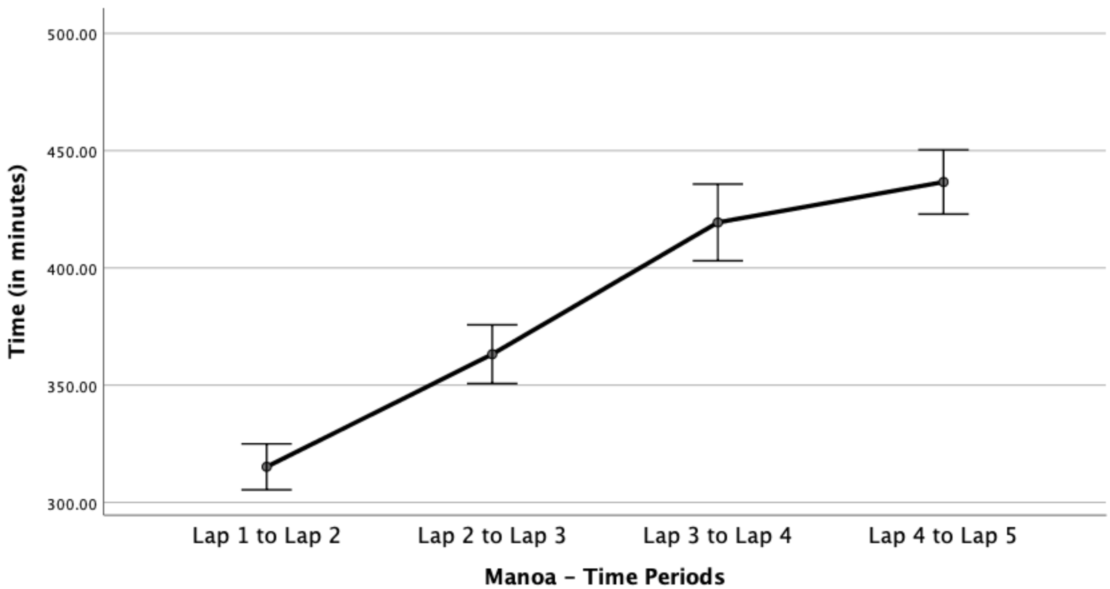
**Table 3. Post Hoc Tests for Significant Interaction – Nuuanu**

| Time Period | Placement Group Reference | Placement Group | Mean Difference (95% CI) | *p*-value |
|---|---|---|---|---|
| 1-2 | $1^{st}$-$21^{st}$ | $22^{nd}$-$42^{nd}$ | -47.12 (-61.41 - -32.83) | < 0.001 |
| | | $43^{rd}$-$63^{rd}$ | -81.04 (-95.33 - -66.74) | < 0.001 |
| | $22^{nd}$-$42^{nd}$ | 43-$63^{rd}$ | -33.92 (-48.21 - -19.62) | < 0.001 |
| 2-3 | $1^{st}$-$21^{st}$ | $22^{nd}$-$42^{nd}$ | -72.88 (-90.35 - -55.40) | < 0.001 |
| | | $43^{rd}$-$63^{rd}$ | -107.47 (-124.95 - -90.00) | < 0.001 |
| | $22^{nd}$-$42^{nd}$ | 43-$63^{rd}$ | -34.60 (-52.07 - -17.13) | < 0.001 |
| 3-4 | $1^{st}$-$21^{st}$ | $22^{nd}$-$42^{nd}$ | -105.20 (-127.61 - -82.78) | < 0.001 |
| | | $43^{rd}$-$63^{rd}$ | -126.81 (-149.22 - -104.39) | < 0.001 |
| | $22^{nd}$-$42^{nd}$ | 43-$63^{rd}$ | -21.61 (-44.02 – 0.81) | 0.059 |
| 4-5 | $1^{st}$-$21^{st}$ | $22^{nd}$-$42^{nd}$ | -71.52 (-93.25 - -49.71) | < 0.001 |
| | | $43^{rd}$-$63^{rd}$ | -71.44 (-93.25 - -49.62) | < 0.001 |
| | $22^{nd}$-$42^{nd}$ | 43-$63^{rd}$ | -0.09 (-21.90 – 21.73) | 0.99 |

**Table 4. Post Hoc Tests for Significant Interaction – Makiki**

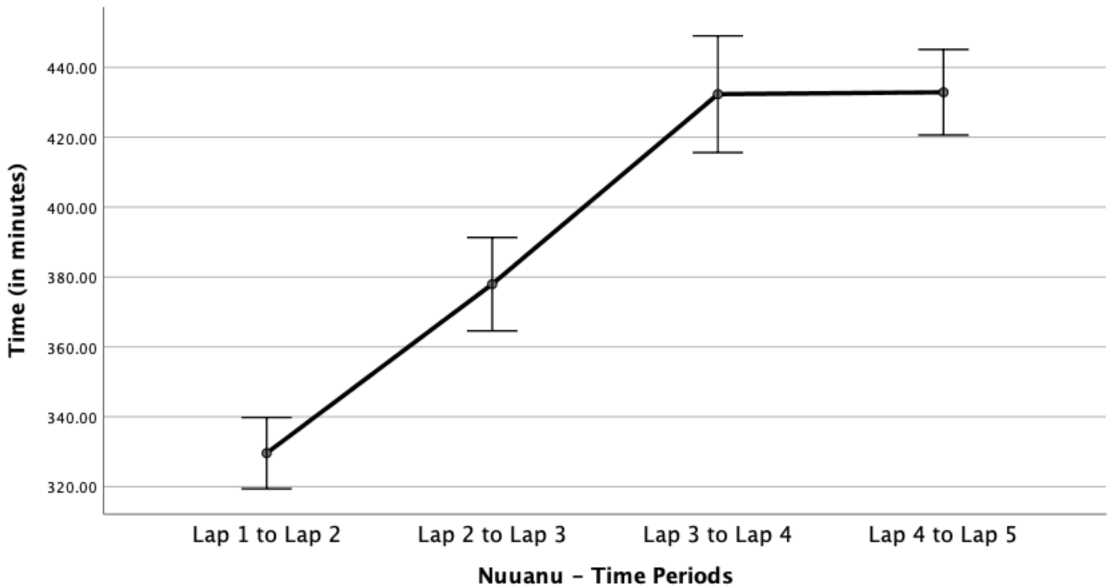
| Time Period | Placement Group Reference | Placement Group | Mean Difference (95% CI) | *p*-value |
|---|---|---|---|---|
| 1-2 | 1st-21st | 22nd-42nd | -57.15 (-71.48 - -42.83) | < 0.001 |
| | | 43rd-63rd | -89.38 (-103.70 - -75.05) | < 0.001 |
| | 22nd-42nd | 43-63rd | -32.22 (-46.55 - -17.90) | < 0.001 |
| 2-3 | 1st-21st | 22nd-42nd | -84.94 (-104.41 - -65.47) | < 0.001 |
| | | 43rd-63rd | -118.93 (-138.39 - -99.46) | < 0.001 |
| | 22nd-42nd | 43-63rd | -33.98 (-53.45 - -14.51) | < 0.001 |
| 3-4 | 1st-21st | 22nd-42nd | -101.16 (-125.31 - -77.00) | < 0.001 |
| | | 43rd-63rd | -111.42 (-135.57 - -87.26) | < 0.001 |
| | 22nd-42nd | 43-63rd | -10.26 (-34.41 - -13.89) | 0.40 |
| 4-5 | 1st-21st | 22nd-42nd | -71.96 (-93.89 - -50.03) | < 0.001 |
| | | 43rd-63rd | -88.19 (-110.12 - -66.26) | < 0.001 |
| | 22nd-42nd | 43-63rd | -16.23 (-38.16 – 5.70) | 0.14 |

**Figure 2. Manoa Main Effect**



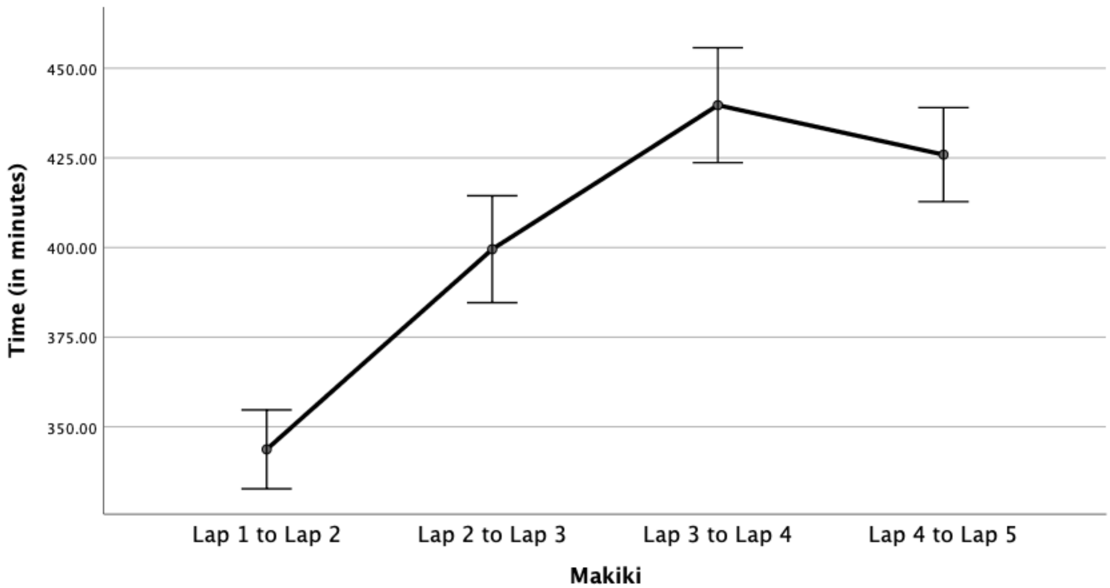

**Post hoc testing determined that there were statistically significant increases in lap time in between laps 1-2 and laps 2-3, laps 1-2 and laps 3-4, laps 1-2 and laps 4-5, laps 2-3 and laps 3-4, laps 2-3 and laps 3-4, $p < 0.001$, as well as between laps 3-4 and 4-5, $p = 0.002$.**

**Figure 3. Nuuanu Main Effect**




**Post hoc testing found statistically significant increases in time between laps 1-2 and laps 2-3, laps 1-2 and laps 3-4, laps 1-2 and laps 4-5, laps 2-3 and laps 3-4, laps 2-3 and laps 3-4, $p < 0.001$, but not between laps 3-4 and laps 4-5, $p = 0.922$.**

**Figure 4. Makiki Main Effect**




**Post hoc testing showed significant increases in time between laps 1-2 and laps 2-3, laps 1-2 and laps 3-4, laps 1-2 and laps 4-5, laps 2-3 and laps 3-4, laps 2-3 and laps 3-4, $p < 0.001$, and then a significant decrease in time between laps 3-4 and laps 4-5, $p = 0.02$.**

**Figure 5. Interaction between Groups and Time Periods for Manoa**

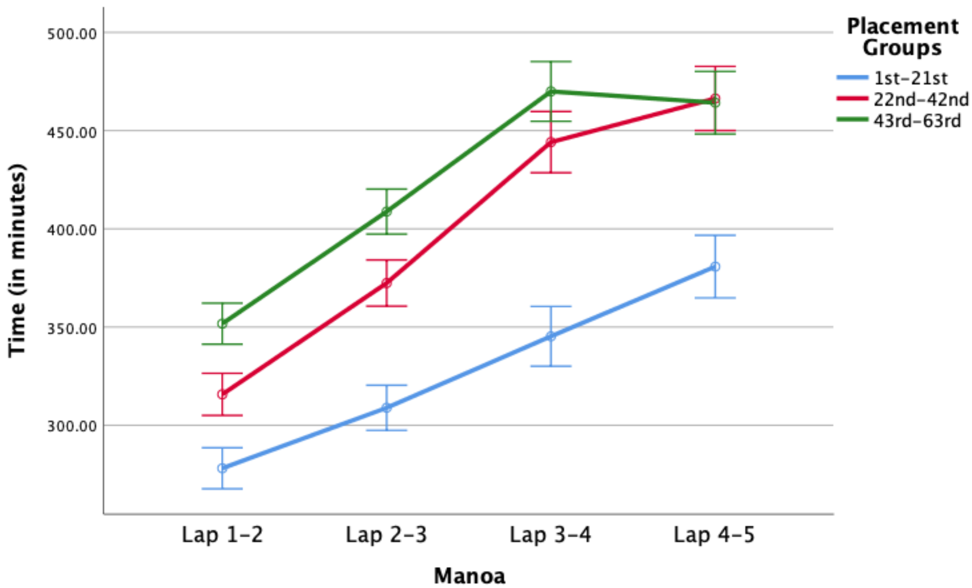



**Figure 6. Interaction between Groups and Time Periods for Nuuanu**

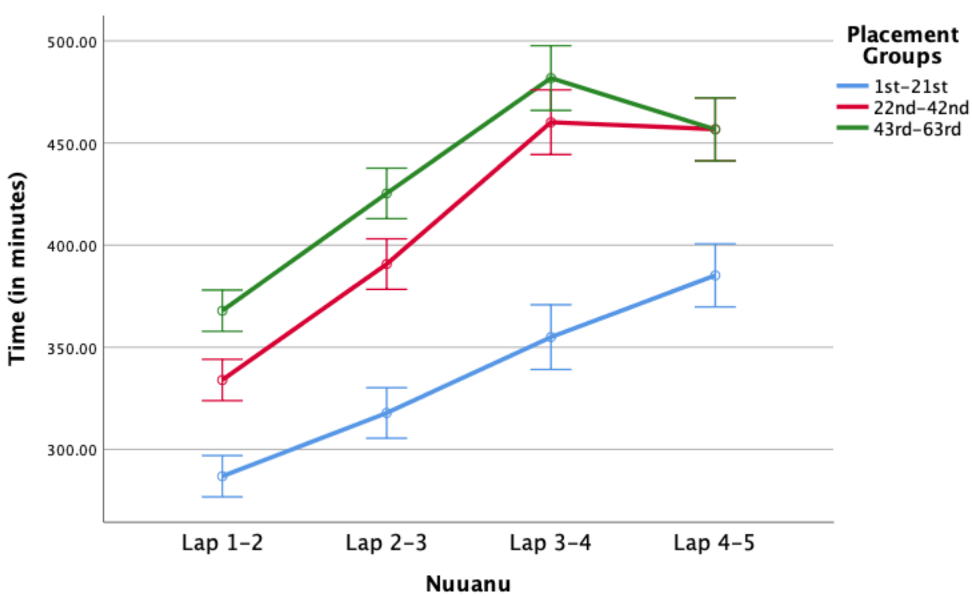
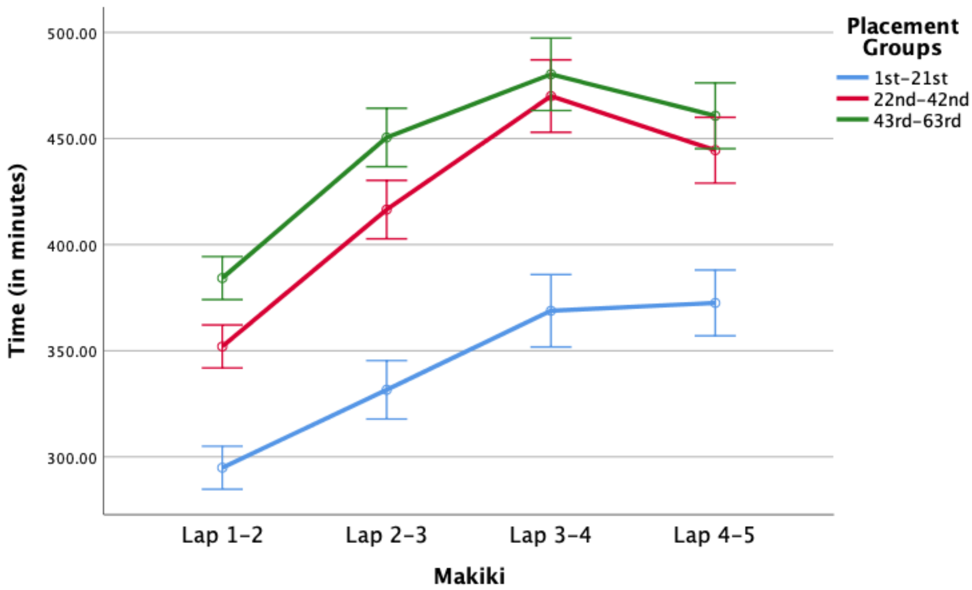


**Figure 7. Interaction Between Groups and Time Periods for Makiki**




## DISCUSSION

### Interpretations/Implications

The goal of this study was to identify and describe the pacing variance among runners competing in a mountainous 100 mile ultramarathon and to determine if faster runners demonstrated greater pacing variance than slower runners and how those changes in variance fluctuated throughout the race. For the race splits associated with the Manoa segment there was a statistically significant effect detected ($p < 0.001$) indicating as a group all finishers significantly increased the amount of time to complete this segment of the course as the race progressed. A similar effect was detected in the analysis of the Nuuanu segment finding a significant increase in time between laps 1-2 and laps 2-3, laps 1-2 and laps 3-4, laps 1-2 and laps 4-5, laps 2-3 and laps 3-4, laps 2-3 and laps 3-4, $p < 0.001$, but not between laps 3-4 and laps 4-5, $p = 0.922$. The Makiki segment analysis was the only segment that demonstrated a significant increase in lap times and then a significant decrease in time between laps 3-4 and laps 4-5, $p = 0.02$. Figure 1, 2, and 3 present the findings of the ANOVA analyses graphically for Manoa, Nuuanu, and Makiki and what is noticeable is when looking at all finishers as they got closer to finishing (laps 4-5) they were able to reduce the trend in increasing time to complete each segment and even significantly increased pace in the final segment of the race (Figure 3). There are a couple of ways to look at this speeding up towards the end of the race. The first could be psychological where the further away the finish is the more conservative runners are with their pacing. Another option is that runners are utilizing their anerobic energy at the end of a long aerobic race. This would align with the idea that the central governor's part in regulating pace and that these athletes have reached a point where they are then able to tap into emergency reserves.

This final speeding up is consistent with previous findings (Kerhervé, Millet & Solomon, 2015) where there is a final increase in pace over the last 10% of the race. This speed reserve could be due to runners conserving until either they have become confident, they will finish the race or that the last perceived challenging section has been completed. Kerhervé et al. (2016) did not demonstrate this final speed reserve phenomenon however their course gradient was not as extreme as it is with the Hurt 100 course or the Ultra Trail Mount Blanc course that was analyzed (Kerhervé, Millet & Solomon, 2015). Both courses in fact end in similar manner with one final significant ascent followed by a downhill/level gradient finish.

The second piece of the analysis focused on how pacing variance differed among finishers based on their ranked performance. Finishers were broken down into three groups: Group 1 ($1^{st}$-$21^{st}$), Group 2 ($22^{nd}$ – $42^{nd}$), and Group 3 ($43^{rd}$ – $63^{rd}$). Statistical analysis of these three groups demonstrated that there were significant differences between pacing in most of the segment comparisons where runners in Group 1 ($1^{st}$-$21^{st}$) regulated their speed and demonstrated less variance (Figures 5, 6, and 7) in pacing than in Group 2 (22nd – 42nd) and Group 3 (43rd – 63rd). This aligns with previous findings that looked at changes in running speed in a road 100km race that also compared competitors by creating groupings based on placement (Lambert et al., 2004). Group 1 did have less variance in pacing overall than Groups 2 and Group 3. Group 1 runners although they demonstrated positive pacing over the course of the race, they slowed down less than Group 2 and 3 similar to what Kerherve et al. (2015) determined with their faster grouping of runners.

Runners in all groups slowed their pace as the race progressed and Group 2 and Group 3 had the greatest degree of pacing variability. Group 2 and Group 3 runners demonstrated more pacing variability when compared to Group 1 including a significant decrease in time between laps 3-4 and laps 4-5. It is possible that runners of these groups could be more focused on the completion of the course within the allotted time (36 hours) versus achieving a higher placement or a faster time which in part would help explain the sudden increase in pace over the last segments of the course. With a race that historically has a finishing percentage of around 50% perceptions of risk could be associated with different approaches to pacing the start of an ultramarathon (Micklewright et al., 2015). Runners pace selection is also influenced by past performances in both training and racing, and this could also play a role when determining an efficient pace/effort during a race of this length and difficulty.

**Limitations**

There are several areas in which this research was limited, and they should be highlighted. This race has a significant amount of time where supplemental lighting is necessary due to the dense forest canopy and running pace can vary depending upon what people have for equipment (headlamps, poles, footwear) and their personal experience running in the dark. Additionally, no previous information about race performance or training details was considered. These are factors that could offer further insight into pacing variability and could have added to further interpretation to this research. It could also prove helpful to know if runners experience any acute injuries during the race as this could significantly alter pacing if they were able manage the injury through to the finish.

Using complete GPS files could also prove beneficial but also problematic as these would be limited in battery life of recording method and accuracy due to both device degree of error and dense forest canopy interfering on this course. With this data however you could then factor in nonmoving time and how that changes through the course of the event. Nonmoving time could be due to several factors including time spent at aid stations, needing medical treatment, or even rest.

Nutrition during the race is an unknown and can have a significant impact on performance and pacing for athletes of all levels. If someone is burning through their glycogen storages and not refueling at a high enough rate, performance can be significantly affected causing someone who could be running faster to slow down due to fueling errors (Pruitt and Hill, 2017). Researchers took on the task of creating fueling equations that factored in an individual athletes Vo2 max and body weight to create an optimal carbohydrate and pacing strategy. There are many reasons why a runner might under fuel during a race of this length and it could be as simple as not knowing the ideal rate of consumption per hour for them personally, to decreased desire to fuel and hydrate due to nausea or other gastrointestinal issue that may arise. Costa et al. (2014) who recorded feedback from 25 ultramarathon runners, found that 65% of the runners reported at least one severe gastrointestinal symptom during the 24-hour ultramarathon race. Any of these, even for a short period of time during the race, could alter overall pacing.

## Recommendations

Apply similar analysis to a larger more competitive race to have a stronger data set. More runners would mean greater distribution of ability levels. Looking at a race such as Ultra Trail Mont Blanc or Western States 100 miler and using several years of split could be a focus for future research. For a race like UTMB with 2,300 runners there is a much larger sample size and a much greater number of elite runners in that field and analysis of multiple years could prove beneficial when looking to identify trends in pacing variance and how they relate to placement and or overall time to complete the course. Research focusing on shorter distances and pacing variability such as the half marathon and marathon have focused on gender differences when it comes to pacing (Cuk et al., 2020) as well as age (Nikolaidis and Knechtle, 2017). Pacing and these factors should be included in future pacing variance research as it relates to 100-mile racing. A pre and postrace survey could also provide additional context that could be valuable specifically when it comes to looking at pacing variance and runners who did not finish the race. A survey tool like one used by Corrion et al. (2018) could be utilized to determine if there is a relationship between pacing variance and a runner's coping abilities and self-efficacy constructs and how those may align with dropping out of a race. This would help construct a more complete picture of each athlete and could provide insight into differences between finishers and non-finishers as well as potential differences between those who place higher versus lower in the finishing results.

In summary, this research shows that in a mountainous 100 mile trail ultramarathon, runners all runners demonstrated positive pacing over the course of the race and that faster runners (Group 1) demonstrated less pacing variance than the slower runners (Group 2 and 3) and finished higher in the overall standings when compared to runners with greater pacing variance. This information could be used by runners competing in races of this distance/difficulty when setting pacing goals in their future events. It could prove beneficial to any runner competing in trail 100 miler to understand that by reducing the variability in their pacing over the course of the entire event could result in a greater performance both in the events rankings and overall time it takes them to complete a race of this distance.

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## BIOGRAPHY OF AUTHOR

Brendan Gilpatrick is a Maine native who graduated from Hebron Academy in 2002 and from the University of Southern Maine in 2006 with a bachelor's degree in psychology. He has raced over 50 ultramarathons ranging from 50km to 100 miles including the HURT 100 Miler which is in part the focus of this thesis. He has been coaching runners of all levels around the country for the past 10 years and was a collegiate coach for 7 years. Brendan is a candidate of the Master of Science degree in Kinesiology and Physical Education from the University of Maine in December of 2021.