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A Quantitative Analysis of Gender Differences in the Improvement of High School Long-Distance Runners

Alexander Whittle

Holmdel High School

ABSTRACT

This paper presents a quantitative analysis of the gender differences in the improvement of high school long-distance runners to better understand the impact of gender on athletic performance. There is a lack of gender-specific studies regarding athletic performance in existing research, especially at the high school level. There is also a clear gap in available research comparing the improvement of males and females. To close these gaps, this research analyzes 1600-meter race times of high school runners from MileSplit, a running time database. These times were imported and analyzed by Python code and Excel graphs. Results reveal that male runners experience greater improvement than females during high school and that elite runners improve at a faster rate than non-elite runners. These results can be connected back to the difference in growth patterns and hormonal processes of each gender. This research addresses gender-based performance differences among high school runners and serves as a basis for future investigations on athletic performance gaps between genders.

Introduction

Males and females have drastically different biological foundations. During puberty, each gender experiences different changes such as weight and height gain, plus the addition of hormones that amplify these changes. These changes contribute to the significant difference in athletic performance between the genders (Costa et al, 2021). However, few studies look at the improvement of athletic performance, especially at the high school level. In this paper, I will analyze the difference in improvement between male and female long-distance runners at the high school level using data from quantitative data scraping, collection, and analysis in Python with additional data analysis and visualization in Excel to characterize the difference in improvement between genders.

Literature Review

Variability of Competitive Performance of Distance Runners

The performance of runners can be impacted by a multitude of factors. For this reason, many runners experience variation in their performances. According to The Department of Physiology and School of Physical Education at the University of Otago (2001), some examples of variables that could impact performance variation include age, gender, speed, and race series (marathon, winter/summer season, cross country) (Hopkins & Hewson, 2001). They conducted a study comparing these factors to performance variation by gathering race times for athletes who have participated in two or more races in a series or season, and then identifying correlations between the reasons for variability and changes in performance between races. In doing so, they found that younger runners had more variation compared to older runners as well as male runners compared to female runners. In addition, it found that the combination of factors with higher variability led to significantly more variation in race times. These conclusions are supported by a multitude of similar studies that investigated reasons for variation in performance (Coletta et al, 2013). However, it is important to note that runners under the age of 20 were not included in this study due to higher variation in race time and smaller sample sizes. Because of this, it is evident that there is missing data on performance of young runners and how different factors of variation impact them, and differences between younger runners and older runners. By investigating factors that impact performance variation, we can better understand what causes variation and what needs to be further investigated to fully understand performance variation for all long-distance runners.

Seasonal Strength Performance and Its Relationship with Training Load on Elite Runners

One major factor that impacts the performance of long-distance runners is training load because of its correlation with hormonal responses. This is a distinguishing factor between male and female long-distance runners due to their significant difference in hormones, according to a study from the Journal of Sports Medicine (Balsa-Fernández, 2015). This study sought to analyze the relationship between strength and training load in elite runners. Training load was assessed daily using distance run, training zones, and session-rate of perceived effort (RPE). Sprint, squat, and basal salivary free cortisol levels were also taken into consideration to better understand how training load and hormonal responses were related. The results of this study highlight the possible benefits of resistance training and the possible ways to avoid injuries from overtraining or "overtraining syndrome" of elite athletes which can shed light on the correlation between training and performance and how this differs between genders. Similar to the study conducted by the University of Otago, this Journal of Sports Medicine study did not include data from younger and less experienced athletes. Because this study focuses on "elites," the results cannot be generalized to long-distance runners of all ages such as high school runners. However, it does introduce the question as to whether or not top high school athletes improve less than the rest of the population due to "overtraining syndrome." Additionally, the sample size of this study included 12 males and 3 females, an example of the minority of female representation in studies conducted on long-distance runners. While this study provides valuable insight on training load and its link to hormonal responses in elite runners, it also highlights the need for more extensive research on long-distance running performance between athletes of different levels.

Gender Differences in Height and Weight Through Adolescence

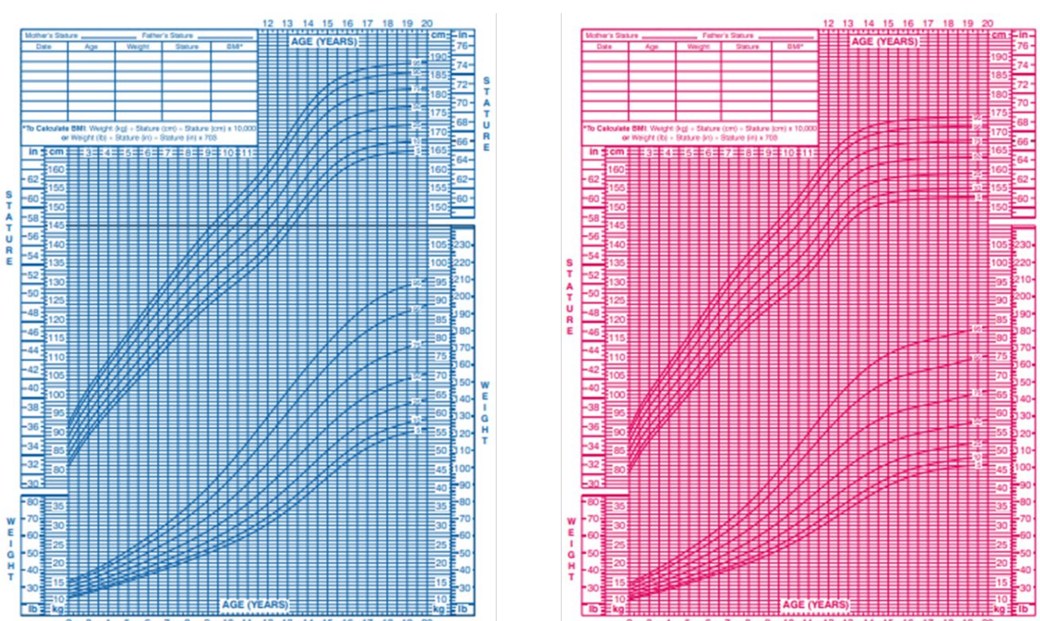

Figure 1. CDC Growth Charts for Boys and Girls ages 2 through 20

The Centers for Disease Control and Prevention publish growth charts (CDC, 2000) that track the growth in height and weight of boys and girls across the various percentiles. From this data, it is expected that a boy at the 50th percentile would grow approximately 6 inches and gain 50 pounds between the ages of 13 and 18. In contrast, a girl at the 50th percentile would grow approximately 2 inches and gain fewer than 10 pounds between ages 13 and 18. At higher percentiles, the girl would grow about the same amount but would gain significantly more weight. The height and weight changes experienced during high school could significantly impact running performance. Unfortunately, most available running performance data does not track height and weight of the runner or even age so it is difficult to correlate performance changes to those metrics.

Influence of Biological Maturity on the Muscular Strength of Young Male and Female Swimmers

In this study conducted on the muscular strength evolution of males and females between the ages of 10 and 20, researchers observed that females showed no significant differences in strength or muscle mass across puberty stages, but males did (Costa et al, 2021). For males, there was a significant increase in muscular strength and muscle mass across the puberty stages that typically are experienced between the ages of 12 and 16. The researchers concluded that in the context of swimming, grouping males by pubertal development levels rather than chronological age was a better choice for training due to the associated significant difference in performance evolution. For females, they concluded that chronological age was sufficient since there was no significant difference in muscular strength or mass and therefore in performance evolution. This study measured the strength and mass of the extensor muscles of the knee across different stages of puberty, which may have a performance correlation in running similar to the one observed by that study in swimming.

Do Gender Differences in Running Performance Disappear with Distance?

Although it is known that gender makes a difference with shorter distance events, it is unclear if that still applies to longer distances. Multiple studies have focused only on males for the sake of consistency, causing many conclusions to be generalized to males only (Knechtle, 2008; Sedano, 2013). One study sought to find out how these generalizations apply to both genders by analyzing data for both genders at both longer and shorter distances (Coast et al, 2004). Prior to performing their research methodology, the researchers of this study believed that gender differences do disappear with distance due to fuel utilization, muscle damage repair after exercise, and natural performance improvement in the past ten years. However, after conducting their research, they found that there were larger differences between gender over longer distances. That being said, this could be due to the lack of women in distance events since there was less available data for females. This study is important for my research because it used existing data to make new conclusions about runners and their improvement which influenced my experimental procedure for my research. In addition, this is one of few studies that mentions the clear difference in the number of females in long-distance events versus males. Due to the reduced number of females in performance-oriented studies, it is difficult to come to concrete conclusions about performance differences between genders in long-distance events, and there is a gap in publicly available research on gender differences in the improvement of long-distance runners.

A Gap in Running Performance Studies

Although there is research on performance variation in long-distance runners, there is little publicly available information on performance differences between genders, especially in younger and less experienced runners such as high schoolers. Many studies have focused only on elite runners or only on males, and thus conclusions made about male long-distance runners may not reliably apply to females, especially at the high school level. Since there is a lack of both female focused studies and comparisons between genders, female performance has been inaccurately perceived the same as male performance (Rosell, 2022). This misconception that the performance of male and female long-distance runners is detrimental to female runners since conclusions derived from male oriented studies do not necessarily apply to them. By evaluating female performance alongside male performance, conclusions derived from male oriented studies could be adjusted to consider female performance differences. This could include improved training targets and techniques.

Methods

The method of my study sought to answer the question *do male long-distance runners improve more than female long-distance runners throughout high school?* I hypothesized that male long-distance runners will experience more improvement than female long-distance runners. In finding the answer to this question, I hoped to provide insight on not only which gender experiences more improvement in their athletic performance, but also why there is a difference in improvement between genders.

Data Source

To answer this question, I needed the running times for runners of both genders throughout their high school careers. MileSplit is a running-focused website that is commonly used to record the race times of high school runners. I used Milesplit because it included all available race times for runners across the nation throughout their high school career which is what I needed to track improvement over time. The specific data I used was a ranked list of each event per gender. While I was debating between the 1600-meter race and the 3200 meter race, I decided to focus on the 1600 meter race since it had more data points. Both events are considered long-distance, and more data points would potentially provide me with more data for analysis. From there I could further manipulate the search parameters of the database to show the top times for each gender in a given state, grade, and year.

Data Collection

To gather the data from MileSplit for analysis, I created code in Python to scrape the data from the website and save it in Comma-Separated Value (CSV) format to facilitate further analysis and comparison using Microsoft Excel. My web-scraping code uses Selenium, an open source browser automation library in conjunction with Chromium ChromeDriver, to emulate browser interactions with the MileSplit web site, including logging in with a username and password and requesting race data by state, event, gender, year, and grade. The MileSplit web site only returns search data one page at a time, for up to 20 pages, with each page listing at most 50 matches in an HTML table contained in an HTML page. My code navigates through all the provided pages to gather all of the information available. This required some experimentation to determine the formats of the queries and data returned as well as understand the timing required to make sure pages are fully loaded, after ads have been retrieved and displayed, before scraping the data. My code uses Pandas, an open-source Python Data Analysis Library, to parse the HTML table and eventually save it into a CSV file. Before saving the data, my code converts the race times from minute and second (mm:ss) format to total seconds, which is easier to work with.

Once the data was available in CSV format, I imported the data into Microsoft Excel. This allowed me to merge data from the freshman and senior years of a given class using an inner join to only consider the senior year times of runners for which freshman year times were available. Using these senior and freshman times, I calculated the time difference between the freshman and senior year best time for a given runner and divided that difference by the freshman time. This represents the decrease in best race time of the season from freshman year to senior year as a percentage decrease between the freshman time and the senior time. Normalizing the data was important since it was expected that the females' absolute times would be higher than that of the males and thus would be more difficult to compare. However, by normalizing the data, the overall improvement as a percentage could be used as a data point for comparison instead. Based on this primary metric, I calculated some descriptive statistics that I could use to confirm normal distribution with high probability and compare the different metrics between males and females.

Method Limitations

One obstacle I came across in my data collection was that I could only access the top 1000 data points for any given search. Each search could specify parameters that I had chosen. I had originally wanted to include all runners despite their state, grade, and year that had enough data points but due to the 1000 data point maximum, using a broad search I would only have access to very elite athletes since the top 1000 didn't include all runners of each gender. To put this into perspective, the 400th male runner in 2022 did not even make the top 1000 list of all time. Because of this, I decided to limit my data collection granularity to data gathered for one year, one grade, and one state. This also allowed me to stay within the 1000 result limit and gather data on all types of athletes rather than only the most elite runners. This helped me get an accurate representation of improvement of a similar timeframe within the smaller data set.

While I had wanted to analyze the most recent data, I noticed that there was a sharp decline in 1600-meter times and data samples in the years 2020 and 2021. This is because many races were canceled during this period due to COVID-19. As a result, I decided to only gather data from 2019 or earlier to avoid inaccurate results due to a much smaller data pool and the effects of training disruption during COVID.

To come to the most accurate conclusion, I wanted to choose runners with a sufficient amount of data. However, I also did not want to limit my data pool to more elite runners who have raced more than amateur runners. For this reason, I only included runners who had had at least one senior-year time and one freshman-year time for the 1600-meter race. This meant I looked at seniors from 2019 and their freshman times from 2016. Since running track is a voluntary activity, there may be inherent success bias in this data since measurements are limited to seniors who ran senior year and also ran as freshman. Runners who may have quit between freshman and senior years having been discouraged by a performance drop off would not be included in my data.

Using this information, I was able to calculate the improvement of each athlete from their freshman to senior years by comparing the athlete's best 1600-meter race time from freshman year to the athlete's best 1600-meter race time from senior year. I calculated the difference in seconds and divided this time difference by the freshman time. This normalization was necessary to allow the male and female data sets to be compared.

Initially I had thought to include race times from sophomore and junior years to consider a more complex trend analysis but in the end decided that the best senior time compared against the best freshman time offered enough insight since the key finding was that during the years between freshman and senior year, males improve significantly more than females do and that the difference was statistically significant.

Data Results and Analysis

The data from MileSplit of the NJ Class of 2019 contains the 1600-meter race times of females as freshman in 2016 (532 data points) and as seniors in 2019 (326 data points). It is interesting to look at the freshman times and senior times separately.

Many human characteristics, such as height and weight, when collected across a large set of people have a normal distribution. A normal distribution is a special probability distribution that has 95% of its data set in a bell curve within 3 standard deviations of the mean, which is centered and equal to the median. From the histograms it is clear that the samples are not normally distributed and instead have a bit of a tail that includes the longer times in the sample. This is not surprising since for a race time it is much easier to find samples that are significantly longer relative to the mean than those that are significantly shorter. Beyond the visual evidence I confirmed the non-conformance of normal distribution by running the Shapiro-Wilk test for normal distribution in python using the SciPy library, which resulted in a statistic of 0.962 and p-value of 2.372e-10. A p-value below 0.05 is generally considered to refute the hypothesis that the data is normally distributed. Even cutting off the tail of the data at 440 seconds would fail a Shapiro-Wilk test for normal distribution with a p-value of 1.791e-05.

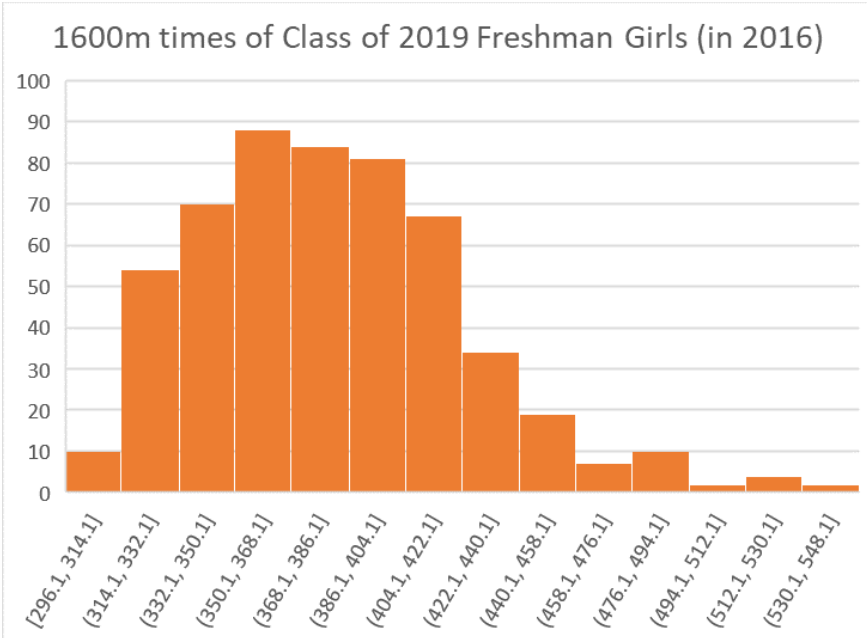

Figure 2. 1600m times of Class of 2019 Freshman Girls

The senior data for this same class is similar in its distribution and again nonconformance to the normal distribution is confirmed using the Shapiro-Wilk normal distribution test. It should be noted that there are more freshman female data points than senior female data points in the Class of 2019, which is not unusual since there is often a drop off in participation between freshman and senior years.

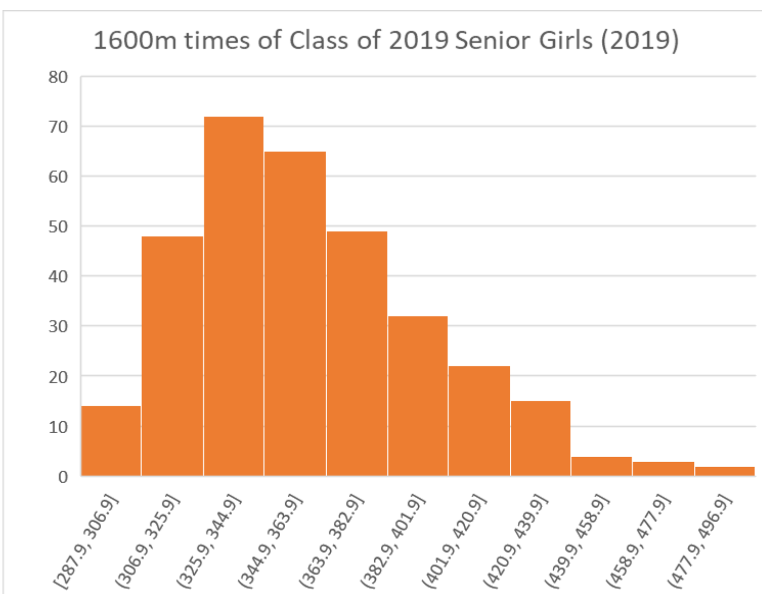

Figure 3. 1600m times of Class of 2019 Senior Girls

From this freshman and senior data, I did an inner join to bring together 2016 freshman and 2019 senior data from the same runner. For the female NJ Class of 2019, there are 148 matches of name and school across the freshman and senior data points. From this data, I calculated the normalized decrease in race time, which is calculated to be senior time minus freshman time, divided by the freshman time. This value is positive if the athlete had improved their time between freshman and senior years. This normalized decrease represents the decrease from freshman to senior year compared to the freshman time and can be displayed as a percentage. The normalization of the time is important in order to be able to compare this normalized decrease with that of another athlete who may have faster times. This is critical when comparing improvement between males and females since males tend to have faster overall times than females.

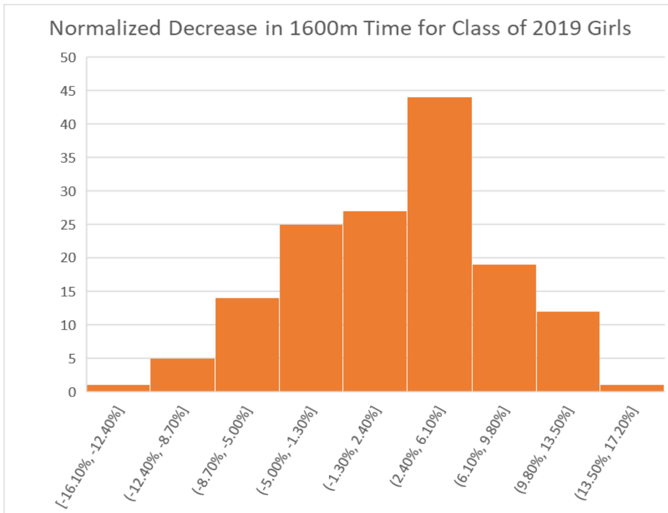

Figure 4. Normalized Decrease in 1600m Time for Class of 2019 Girls

Similarly, analogous data was available for the males as freshman and seniors to yield the normalized decrease for the Class of 2019 Boys.

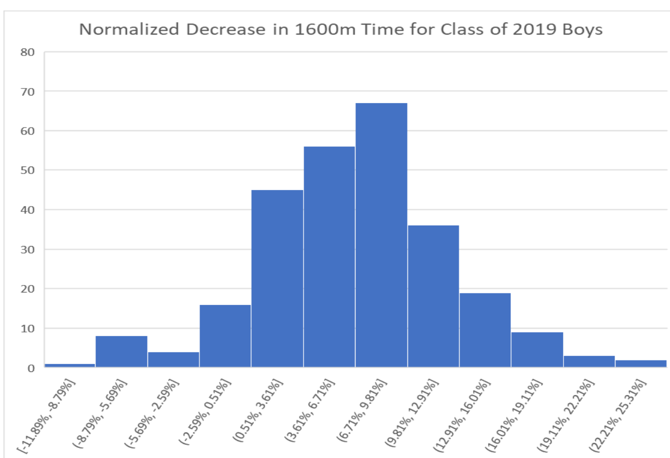

Figure 5. Normalized Decrease in 1600m Time for Class of 2019 Boys

Looking at the histograms, the shapes look similar, more symmetric than the race data alone, and closer to normal distribution. Bringing both histograms together on a single chart, normalizing the y-axis to represent percentage of sample count rather than sample count to account for the different sample sizes between genders, it is clear that the male curve is to the right of the female curve indicating a higher normalized decrease in time and thus a bigger performance improvement. This is not surprising given that the key indicators from the two data sets, such as mean and standard deviation also indicate the higher overall improvement among males.

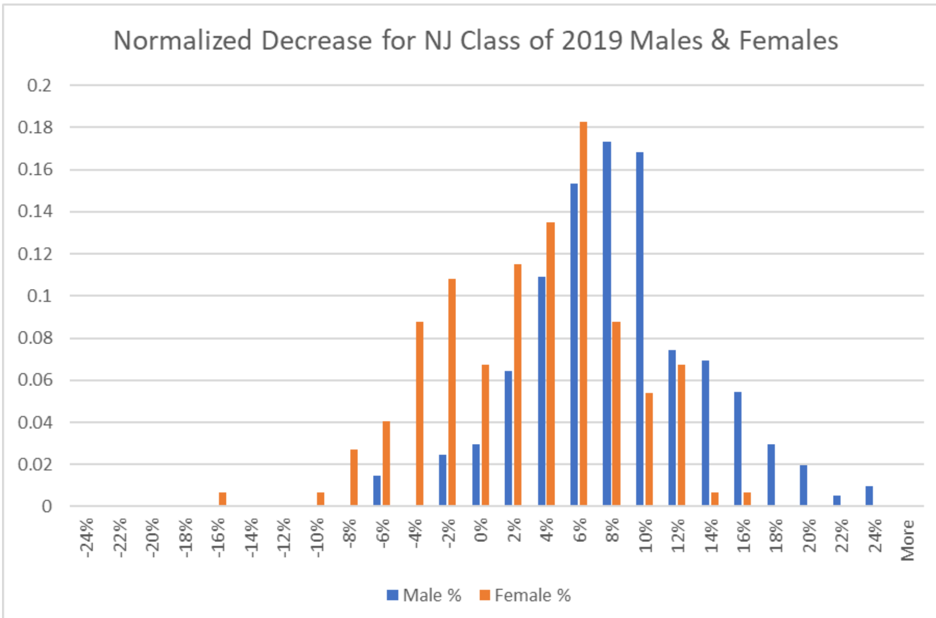

Figure 6. Normalized Decrease for NJ Class of 2019 Males & Females

NJ Class of 2019	Females (148)	Males (266)
Average	1.87%	6.71%
Standard Deviation	5.60%	5.63%
Average Top 25	5.09%	8.52%
Standard Deviation Top 25	4.38%	4.49%
Average Top 50	4.42%	8.24%
Standard Deviation Top 50	4.06%	4.27%

By collecting and correlating the proper data, I was able to calculate and compare the improvement factors for each gender. In the end, there were 148 females and 266 males in NJ who were seniors in 2019 and had a freshman time in the 1600-meter race to compare. Overall, across all females, the average improvement was 1.87% as compared to the average improvement of males of 6.71%. Looking at the top 25 for each gender, females had an average improvement of 5.09% while males had an improvement of 8.52%. The top 25 of each gender had more improvement than the top 50 and more than the entire population as a whole. Part of the reason for looking at the top runners was the conjecture that there is more variance in the data from athletes that are new to running.

These results support my hypothesis that high school long-distance male runners experience more improvement than females. Males did in fact have more improvement than females. This can be seen in the graph above because the male distribution is to the right of the female distribution. From this graph, the difference between the improvement of each gender is clear and easy to conceptualize. Next, I wanted to see if this finding would be similar for data of a different year. I used the same approach to analyze the NJ Class of 2018, yielding a similar result.

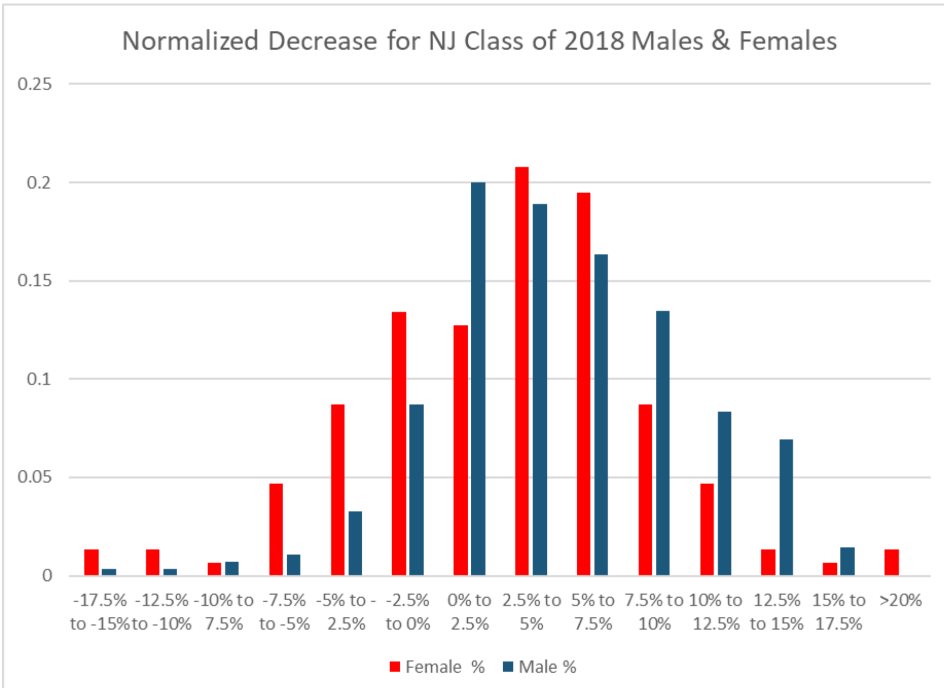

Figure 7. Normalized Decrease for NJ Class of 2018 Males & Females

NJ Class of 2018	Females (149)	Males (275)
Average	2.82%	7.31%
Standard Deviation	5.92%	5.10%
Average Top 25	6.40%	8.99%
Standard Deviation Top 25	3.63%	3.45%
Average Top 50	5.11%	7.84%
Standard Deviation Top 50	4.71%	3.91%

Looking at the NJ Class of 2018 data, it was notable how similar the differences in average between males and females were relative to the same data for the NJ Class of 2019. The improvement of the top 25 and 50 were also aligned.

Next I wanted to see if I would see the same results with data from another state. Changing the state from New Jersey to Pennsylvania again yielded a similar result, as the analogous histogram for the Pennsylvania Class of 2019 shows.

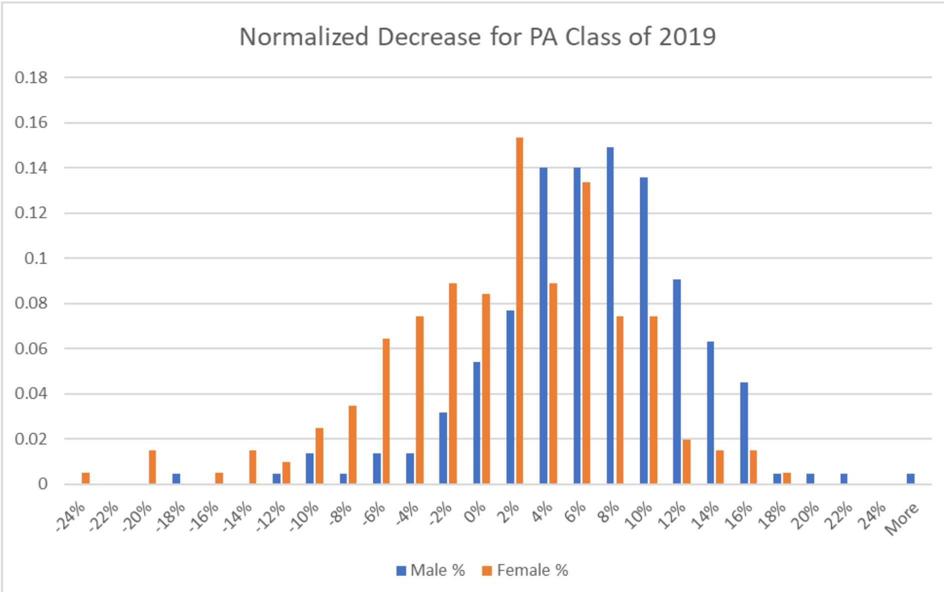

Figure 8. Normalized Decrease for PA Class of 2019 Males & Females

PA Class of 2019	Females (202)	Males (221)
Average	0.33%	5.74%
Standard Deviation	7.20%	5.99%
Average Top 25	5.60%	8.34%
Standard Deviation Top 25	3.61%	2.75%
Average Top 50	4.73%	7.91%
Standard Deviation Top 50	4.34%	3.30%

Once again, it was notable how similar the differences in average normalized decrease between males and females were across the three data sets. The males in all three datasets had a roughly 5% higher average normalized decrease than the females overall and roughly 3% higher for the top 25 or 50.

It was fairly clear visually from the histograms and even numerically from the mean and standard deviations that the male dataset differed from the female one. The next step was to try to prove that the two populations, male and female, were different in a statistically significant way.

Characterizing Distribution

There are several tests available to compare normal distribution probability functions. If I could confirm that the data was normally distributed, I could use one of them.

Visually from the Normalized Decrease histograms for NJ Class of 2019 Females or Males it would appear that the data was roughly normally distributed but may require the removal of some outliers. There are a few indications of normal distribution that I explored:

- Visual histogram compared with bell curve or analogous % bins
- Values of skewness and kurtosis parameters within a range. Note that these metrics seem to only mildly indicate rather than prove normal distribution.
- Passing the Shapiro-Wilk test

The Shapiro-Wilk test is the most rigorous among these. I wanted to see if the data would pass as is or if it could pass if some outliers were removed.

First, I tried the 2019 Female Normalized Decrease with no outliers removed. The Shapiro test returned statistic=0.9875, p-value=0.2064. A p-value of greater than .05 will fail to refute the hypothesis that the data is normally distributed.

Next, I tried the 2019 Male Normalized Decrease with no outliers removed. The Shapiro test returned statistic=0.9888 and p-value=0.0372, which had a p-value below .05 but did not seem far from passing. I removed the 3 most negative outliers that were 3 standard deviations away from the mean and without these outliers the Shapiro test passed with statistic=0.9914, p-value=0.1278.

Population Comparisons

Using the adjusted data, I could compare the two normal distributions using a t-test. The results show that the populations are significantly different with high probability as indicated with the two tail probability, highlighted in yellow, being much less than .05.

t-Test: Two-Sample Assuming Unequal Variances	Males w/o Outliers NJ Class of 2019	Females NJ Class of 2019
Mean	0.069003609	0.018685588
Variance	0.00289972	0.003134591
Observations	263	148
Hypothesized Mean Difference	0	
df	295	
t Stat	8.866666824	
P(T<=t) one-tail	3.66814E-17	
t Critical one-tail	1.650035304	
P(T<=t) two-tail	7.33627E-17	
t Critical two-tail	1.968038115	

Using the same approach, I compared the Class of 2019 Males in Pennsylvania vs New Jersey, and as expected, they were not shown to be significantly different, as indicated by the two-tail probability of greater than .05.

t-Test: Two-Sample Assuming Unequal Variances	PA Males Class of 2019 w/o Outliers	NJ Males Class of 2019 w/o Outliers
Mean	0.060189087	0.069003609
Variance	0.003052556	0.00289972
Observations	218	263
Hypothesized Mean Difference	0	
df	458	
t Stat	-1.76191437	
P(T<=t) one-tail	0.039375423	
t Critical one-tail	1.648187415	
P(T<=t) two-tail	0.078750847	
t Critical two-tail	1.965157098	

I then found, as expected, that all pairs of the three Male groups, PA 2019, NJ 2019, and NJ 2018 were not found to be significantly different, meaning that the samples could be assumed to be from the same population. Similarly all pairs of the analogous Female groups were not found to be significantly different. Finally, all Male-Female pairs were found to be significantly different.

Data Limitations

The analysis was only as good as the data available. I felt that the NJ MileSplit data was good in terms of having lots of data, representing many people. The data of other states in MileSplit were not as good. For example, I had originally planned to use New York as another state to compare but its 2019 data seemed to be incomplete, only having 64 females vs 861 males.

In general, there is more male data than female data, although to a lesser degree. This could in part reflect a larger population of male runners. However, this discrepancy if it indicates insufficient data for females could affect the quality of the female data. Furthermore, the data available can only represent the competitive running population rather than high school students as a whole since its data is based on races.

Finally, there may be self-selection bias inherent in sports data where only people who are thriving in a sport would continue to participate and thus would skew the comparative data across several years. In the case of this study, this could miss data from runners that became slower over time. Data from a mandatory gym class would be more likely to better represent the population as a whole.

Conclusion

In all comparisons attempted, regardless of state difference or year, and also in every quartile, there was a statistically significant difference between the male and female populations in terms of decrease of race time between freshman and senior years divided by freshman time. Furthermore, there was no statistically significant difference between populations of the same gender from state to state or year to year. While this was, to some degree, expected since the difference between males and females was expected to be greater than the differences across state or year, it was encouraging to see it so consistently confirmed.

Even though these results were consistent with my hypothesis, this does not imply that males always experience more improvement than females but does imply that they are more likely to.

There were multiple limitations to my procedure that may have impacted my results such as how I gathered my data. I only gathered data from MileSplit for a small number of years and I did so for each state separately. This procedure was meant to include the performances of athletes of all experience levels yet MileSplit is not reflective of all high school runners and their performances. In addition, by gathering the data for only a small number of years I am unable to reliably say if this trend has been the same for many years or is changing. Therefore it is difficult to project the trend into the future.

Despite these limitations, this research does contribute to the larger pool of relevant research on this topic. High school runners can now better understand the impact of gender differences in their improvement and coaches can take steps to consider this in training. With more time and resources, others interested in this trend can investigate how this relationship has changed over time and how it might change in the future.

Although the results of my research were consistent with my hypothesis, the limitations suggest that further research on a wider participant pool may provide more accurate results or additional insights. It would be helpful to extend this research with additional measurements like age, height, and weight that could help explain or at least correlate to differences in performance. Further research could also add measurements based on puberty or body type metrics which may be a better metric than the grade the student is in.

Other possible extensions would be to extend the age range to the college or middle-school population to quantify improvements there. A future study could also incorporate analysis of individual changes throughout high school with finer granularity than best senior and freshman times. Finally, it would be interesting to analyze subpopulations such as top or elite runners to see if the results of the larger group would be replicated. Though there are multiple future studies that can be conducted to further enhance the results of this research, this study is a good introduction to the comparison of athletic improvement between genders.

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