

# Journey to Paris 2024: A Bayesian Approach to Finding the Best Men's and Women's U.S. Gymnastics Teams

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## Introduction

The Olympic Games are a highly anticipated world-renowned multi-sporting event that takes place every four years. Particularly the Summer Olympic Games tend to have a wider variety of 32 sports and more viewers than that of the Winter Olympics (Olympics, 2021). Athletes from all over the world can participate granted they meet the criteria established by their nation's Olympic committees and the international sports federations. With female qualifying gymnasts from the United States placing with medals in the team all-around, individual all-around, and each individual apparatus in the 2020 Tokyo Olympics game, there has been a surge in media attention on the United States gymnastics teams (Olympics, 2020).

As the Paris 2024 Summer Olympic Games is approaching, the United States Olympic Men's and Women's Artistic Gymnastics aims to put together a team of 5 each that best represents the country on the world's sporting stage by optimizing medal success amongst the team all-around, individual all-around, and individual apparatus events. At the Paris Olympics, there are specific rules about the number of athletes and countries allowed to compete in the events, the low number of athletes that qualify for the finals suggests there must be thoughtful crafting of the team of 5 (UCSAS, 2023). This study aims to use the most recent Olympic Games and other world competitions' qualifying and final round results data to best assemble a team that is likely to produce optimal success in terms of medals within the Olympic qualifiers and final criteria (UCSAS, 2023).

The UConn Sports Analytics Symposium provisioned two data sets on results of teams worldwide that participated in major gymnastic competitions between 2021-2023. Observations were gathered at the athlete/apparatus level scores. It is worth noting, that the data from the 2021 Tokyo Olympics only include results for women's gymnastics, while the data from 2022-2023 include results for both men's and women's gymnastics, so we will not be proceeding with the Tokyo Olympics dataset (further age-based reasoning of not using the Tokyo dataset in Appendix). The data are collected from the results on each corresponding competition's official website. Variables in the data sets include athlete name and gender, country, date of competition, competition, round (qualifier or final of an individual apparatus, individual all-around, or team event), location, apparatus (women compete in "BB": balance beam, "FX": floor exercise, "UB": uneven bars, and "VT": vault; men compete in "FX" and "VT", then HB": high bar, "PB": parallel bars, "PH": pommel horse, "SR": still rings), the execution score, difficulty score, penalty, and final score for that athlete on that apparatus, and the rank of that athlete.

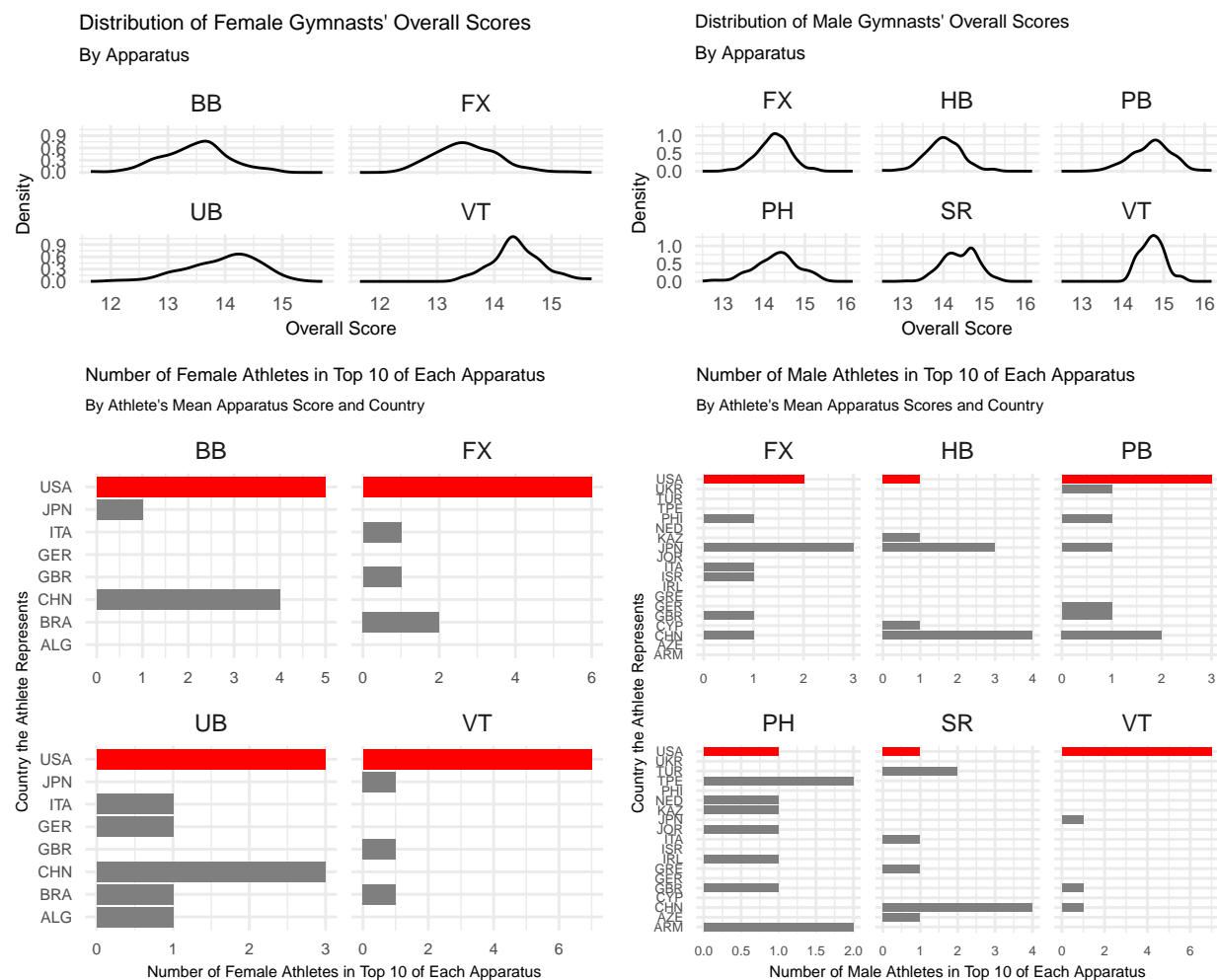
We have the following objectives for this study: (UCSAS, 2023)

- 1) Decide on whether to maximize total medal count, gold medal count, or a weighted medal count
- 2) Decide on whether to value the medals of an event (team, individual all-around, individual apparatus) over others.
- 3) Decide on whether Team USA should maximize its total medal count by selecting a team of five gymnasts who are all-around gymnasts, event specialists (gymnasts who focus on 1 or more apparatus but not all apparatus), or a combination of those.
- 4) Identify the group of five athletes who will most likely enable the Team USA Olympic Men's and Women's Artistic Gymnastics team to maximize medals won in the Paris 2024 Summer Olympics.

Addressing these objectives will assist the national Olympic Artistic Gymnastics teams in best approaching the Olympic gymnastics events in totality by offering recommended strategies to best approach team selection. In our analysis of the best fit US male and female gymnastics teams for the Paris Olympics, we will undertake a Bayesian approach to simulate outcomes of individual athletes' scores in an apparatus. Bayesian frameworks in sports analytics to simulate athlete's results are well-documented and have seen a rise in popularity in the past decade (Santos-Fernandez, et. al., 2019)–for instance, a Bayesian time series regression model to predict winning time distributions and the probability of winning for swimming in the 2020 and 2024 Olympics (Wu, et.al., 2021). We will build upon these analyses and choose the appropriate Bayesian method to simulate outcomes of gymnast results in each apparatus, after which we will analyze the top performers in each apparatus, assign medals, and find the best combination of athletes.

Exploratory Data Visualizations

We find that from the density plots of male and female athletes' overall scores per apparatus that the scores are approximately normally distributed for the apparatuses for both genders. There are some slight deviations from normality; nonetheless, the approximate normality of the distribution of athlete's scores by apparatus informs our Bayesian approach. Furthermore, we plotted the number of athletes per country with the 10 highest average scores for each apparatus internationally. These plots help inform us of if we should be thinking about specialists or generalists in the US team combinations. We see that the top 10 for each apparatus have a high concentration of US female gymnasts, so we may want specialists in our team makeup, whereas that case does not transfer to the US male gymnasts, as there are few US male gymnasts in the top 10 for the floor exercise, high bar, pommel horse, and still rings apparatuses. This is discussed further in the results section.



## Methodology

Prior to conducting simulations, we cleaned our data set on the 2022-2023 gymnastics competition results. Our data set cleaning semantics—wording, combining observations, etc. are in the appendix. We then proceeded to minimize the number of observations in our data set because we felt that it was unnecessary to simulate scores for athletes that had little to no chance of ever medaling in the Olympics given their previous records. To filter the observations, we first removed any individual athletes entirely who had never made the finals in any event in any competition in the data set. Afterward, we created quantiles of 20% increments and 10% increments for each round in a competition for each apparatus, separated by gender because men and women compete separately. We checked the number of unique athletes that competed at each competition in each round (see Appendix), and found that for all rounds in competitions other than the Oceania Championships, at least 36 unique athletes participated. For some rounds, hundreds of athletes participated—so we decided to filter for: if more than 100 athletes competed in a round in an apparatus, then we filtered for athletes’ scores in the top 10%; if less than 100 athletes competed in a round in an apparatus, then we filtered for athletes’ scores in the top 20%; for the Oceania Championships, we filtered for the top 40% (four athletes). The reason we adopted a quantile-based filtering approach is because of the variation in number of athletes who competed at different competitions, so simply taking the top 20 athletes, for example, of each competition may not account for that variation. Our last method of filtering was to remove observations of athletes’ scores for apparatuses if an athlete had not competed more than twice in that apparatus in the entire 2022-2023 data set. Our rationale was that there were 37 distinct competitions in the data set, so if an athlete has not competed more than twice in the past two years in an apparatus, they are likely not that active in that apparatus. At this point, the issue arises that a plurality of athletes has only ever done a single competition in any given apparatus, resulting in a large number of athletes with 0 variances and skewing the distribution. Due to the unlikely nature of athletes who do not compete regularly participating in the Olympics, we have decided to truncate the apparatus level data set to exclude athletes with less than three competition appearances for that given apparatus. We are left with 2210 observations in our filtered data set to conduct simulations, with 157 unique male athletes and 88 unique female athletes.

## Bayesian Monte Carlo Approach

In this study, we present a Bayesian statistical Monte Carlo approach to select the top male and female American gymnast candidates for participation in the 2024 Olympics. Our method involves the creation of prior distributions based on general historical performance data, conditioning these distributions on individual competition results, and simulating medal outcomes by predicting scores for each gymnast in each apparatus event. This approach incorporates both prior beliefs and observed data to make informed predictions about athletes’ performances in simulated events (Hoff, 2009). Utilizing Bayes’ law for probability density functions, where  $x$  is a vector of all the data from an apparatus and gender combination,  $x_i$  represents the vector of observed data for athlete  $i$ , and  $\theta$  represents the parameters of the distribution we will be using to model the competition. We are under the assumption that all gymnastic scores are independent and identically distributed for every athlete and that every athlete’s scores come from the same distribution type. Furthermore, for modeling purposes, we assume a common prior  $p(x|\theta)$  for all athletes such that  $p(x_i|\theta) = p(x|\theta)$  for all  $i$ . Our posterior distribution is:

$$p(\theta|x_i) \propto p(x|\theta)p(\theta)$$

To simulate a score for an athlete we sample  $\theta^{(s)} \sim p(\theta|x_i)$  from the posterior and then sample  $\tilde{x}_i \sim p(x|\theta^{(s)})$ . This represents a new predicted data point for athlete  $i$ , a common practice for estimating values from a posterior predictive distribution in Bayesian Monte Carlo Simulations (Hoff, 2009). Thus, given we can simulate an athlete’s scores, we can then simulate a competition between all candidate athletes and allocate gold, silver, and bronze medals to the top three athletes.

## Prior Distribution Creation and Conditioning on Individual Results

We began by creating prior distributions for each apparatus' total score. See Exploratory Data Visualizations for the apparatus-gender level distribution. Various distributions were considered, but the normal distribution was chosen for ease of use and effective fit with low standard errors and p-values  $< 0.01$ . We depended on conjugacy to derive the parameters of the normal distribution. Since both the mean and variance of the normal distribution are unknown, we used a normal-inverse gamma prior.

To estimate prior parameters, we fit a normal distribution to the distribution of athletes' means and an inverse-gamma distribution to athletes' variances. We used the maximum likelihood method in the `fitdist()` function (Muller, 2023). The maximum likelihood estimates were then used as the prior parameters for the normal-inverse gamma distribution. This process was done independently for all apparatuses and genders. Following the establishment of the prior distributions, we updated these distributions based on individuals' competition results. We rely on existing literature for the formulas for the posterior parameters (Hoff, 2009). We then employ a Monte Carlo method to sample new data, simulating the posterior parameters for mean and variance and then using these to simulate individual gymnastic scores.

## Simulation of Gymnastics Events

To simulate gymnastics events, we performed 500 iterations for each apparatus event, resulting in about 11 million simulated scores. For every iteration, we sampled a score for each athlete,  $\tilde{x}_i$ , from the posterior normal distribution. Furthermore, we truncated the normal distribution at 0 and 20 to reflect the scoring system. We then ranked the athletes by their simulated scores and awarded gold, silver, and bronze medals to the top three athletes. Notably, we chose not to go with a qualification structure and had a simple one-shot round for victory. This decision was made due to computational constraints and was accounted for when identifying Team USA athletes.

## Assumptions

We assume that gymnastic scores are normally distributed and conditionally independent on the athlete. Additionally, we assume independence between apparatus, allowing us to treat each apparatus event as a separate and identically distributed random variable. We also assumed that athletes prioritize all stages of every event identically. Furthermore, we assume that historical performance data adequately represents the gymnasts' true abilities and that changing age is not a factor in gymnastic ability. While this assumption simplifies the modeling process, it may not fully capture the complexities of individual development and improvements over time.

## Results

We ran simulations for each apparatus for each gender (women's 4 apparatuses and men's 6 apparatuses) 500 times, then outputted the top athletes by medal count per apparatus.

### Female Athletes' Results

For women's apparatuses, we outputted the tables of simulation outcomes for floor exercise because of the high presence of medals for US gymnasts. The table of simulation outcomes for other apparatuses are in the appendix.

Table 1: Women’s Floor Exercise Simulation Results

Athlete & Country	Gold	Silver	Bronze	Total Medals
Simone Biles: USA	186	85	57	328
Rebeca Andrade: BRA	38	45	38	121
Kaliya Lincoln: USA	30	37	29	96
Jessica Gadirova: GBR	14	27	43	84
Flavia Saraiva: BRA	27	25	18	70
Jade Carey: USA	22	19	23	64
Martina Maggio: ITA	11	18	29	58
Jordan Chiles: USA	12	20	19	51
Joscelyn Roberson: USA	10	17	20	47
Sabrina Maneca Voinea: ROU	11	15	14	40

For the women’s gymnastics team, we select Simone Biles, Zoe Miller, Shilese Jones, Konnor McClain, and Jade Carey to represent the US at the Paris Olympics. Our rationale for this combination and our framework for optimizing gold medal count, total medal count, and apparatus vs. individual all-around vs. team event wins are explored further in the discussion.

Based on our 500 simulations, Simone Biles has the highest count of total medals in balance beam (170 total medals), floor exercise (328 total medals), and vault (328 total medals), as well as highest gold medal count in floor exercise and vault (186 and 151 gold medals expected of 500 simulations, respectively). Therefore, Biles is expected to be a strong US contender in the individual apparatus events, individual all-around events, as well as a the team all-around since only three members compete in each apparatus for that event. For uneven bars, US athletes Zoe Miller and Shilese Jones come in third (35 gold medals) and fifth place (32 gold medals) respectively. Additionally, Konnor McClain comes second highest for gold medal count for balance beam (65 gold medals) in simulation outcomes, after Yaqin Zhou of China, and Jade Carey comes in third for highest count of total medals (199) and gold medals (61 medals) for vault. Among the simulation results, we generally see the US women gymnasts place very highly in individual apparatuses by both total medal count and gold medal count.

## Male Athletes’ Results

For men’s apparatuses, we outputted the table of simulation outcomes for parallel bars because of the high presence of medals for US gymnasts relative to the other apparatuses. The tables of simulation outcomes for other apparatuses are in the appendix.

Table 2: Men’s Parallel Bars Simulation Results

Athlete & Country	Gold	Silver	Bronze	Total Medals
Jingyuan Zou: CHN	133	75	49	257
Lukas Dauser: GER	43	40	36	119
Boheng Zhang: CHN	25	26	27	78
Curran Phillips: USA	24	20	24	68
Colt Walker: USA	20	28	19	67
Kaito Sugimoto: JPN	23	25	17	65
Joe Fraser: GBR	24	17	19	60
Carlos Yulo: PHI	16	20	22	58
Cong Shi: CHN	15	17	12	44
Blake Sun: USA	15	10	19	44

For the men’s gymnastics team, we select Asher Hong, Curran Phillips, Donnell Whittenburg, Colt Walker, and Brody Malone to represent the US at the Paris Olympics. Our rationale for choosing this combination and optimizing for all-around gymnasts as opposed to event specialists are explored further in the discussion.

We see from our simulation outcomes tables that the US men gymnasts do not come in the top 3 simulated rankings by total medal count for any apparatuses other than Asher Hong in vault, who comes in a simulated second place. As a result, it may not be fruitful to pick individual US male athletes by their apparatus-specific performance, given athletes from other countries are likely to place ahead of them on individual apparatuses. It is worth noting

the overlap of US men gymnasts who place in the top 10 of simulated total medals across the apparatuses. Curran Phillips places in sixth in simulated total medals for vault (112 medals) and fourth in simulated total medals for parallel bars (68 medals). Donnell Whittenburg places seventh in simulated total medals for still rings (56 medals), eighth for simulated total medals in floor exercise (43 medals), and seventh for simulated total medals for vault (111 medals). Colt Walker places ninth in simulated vault total medals (85 medals), fifth in parallel bars simulated total medals (67 medals), ninth in floor exercise simulated total medals (40 medals). Lastly, Brody Malone places fourth in simulated high bar total medals (72 medals) and tenth in simulated floor exercise total medals (39 medals). Because we see that these athletes are still able to place well in multiple events, all the apparatuses except for pommel horse are covered with at least one athlete who performs well in it, but who can also place well in other apparatuses.

## Discussion

### Objective 1: Choice of Medal Success Metric (Total Number of Gold Medals)

From the dot plot visualizations of the women's simulation of the three considered success metrics (gold medal count, total medal count, and weighted medal count) for each apparatus by USA and non-USA teams, there looks to be at least one USA athlete that places higher than of all non-USA athletes in each medal metric for each apparatus except uneven bars (Appendix: Image 5). The women's USA team makes up 51% of the total women's gold medals in the simulation which is a higher proportion than the 47% of the total medal count and 48% of the weighted medals (Appendix: Image 7). From the dot plot visualizations of the men's simulation of the three considered success metrics, for each apparatus by USA and non-USA teams, there are non-USA athletes for each apparatus that exceed the USA in each medal success metric (Appendix: Image 6). The men's USA team makes up 24% of the total medal count in the simulation which is a higher proportion than the 21% of the total gold medal count and 23% of the weighted medals. (Appendix: Image 8) When viewing the top 5 most successful female athletes (top 5 most decorated by that medal metric) in each apparatus for each medal success metric, the USA makes a good portion of these athletes. There tend to be 2-4 USA athletes in the top 5 depending on the success metric and apparatus (Appendix: Image 7). When viewing the top 5 most successful male athletes in each apparatus for each medal success metric, there tend to be 0-3 (mostly 0) US male athletes present (Appendix: Image 8).

Considering that US' female athletes tend to enjoy more successes, regardless of metric, than male USA athletes, it is best to prioritize the success metric that the female team performs the best in. Also viewing the male top 5 most decorated athlete by each metric for each apparatus, the men's USA team has a higher proportion of athletes in the top 5 when using the total number of gold medals as a success metric (Appendix: Image 8). Therefore, the success metric that we aim to maximize to best ensure the USA team's success is the total number of gold medals.

### Objective 2: Value of Medals for Each Event Type (Team AA > Individual AA > Individual Apparatus)

From the table of the top 10 most decorated gold medal female athletes by apparatus from the simulated data, the USA, China, Brazil, and Great Britain make multiple appearances. The USA has athletes in the top 10 most decorated gold medalists for each apparatus as well as the top 5, but other countries do not (Appendix: Image 9). In this case, valuing the team's all-around medal more than the individual all-around and individual apparatus will hopefully increase medal success in terms of gold medal count. When viewing the top 10 most decorated gold medal female athletes by apparatus, the USA's Simone Biles, appears in the balance beam as first, in floor exercise as first, in uneven bars as ninth, and in vault as first. Valuing the individual all-around events higher also may help team USA increase in our metric of success. Furthermore, since these events are harder to achieve than individual apparatuses because of the multiple sections within the event that need to also meet a standard, it will be harder for other countries to also benefit from this increased value.

From the table of the top 10 most decorated gold medal male athletes by apparatus, the USA, Japan, and China make multiple appearances. The only country that has an athlete in each apparatus for the top 10, is the USA (Appendix: Image 11). It could be beneficial for the men's team to value the team's all-around success more

than other events. The US men's team also does not have a well-rounded athlete that places in the top 10 most decorated gold male athletes for each apparatus so we can assume valuing individual all-around successes over the other events would not help the US men's team but it also would not hurt it since other countries also do not have a highly decorated well-rounded competitor.

In the dot plots of the top 5 decorated gold medal female athletes' countries by number of gold medals for each apparatus, US athletes make multiple appearances (Appendix: Image 10). In the dot plots of the top 5 decorated gold medal male athlete's countries by number of gold medals for each apparatus, US athletes are present in multiple apparatuses but not many athletes are well decorated within each apparatus. But in vault there are two US athletes in the top 5 (Appendix: Image 12). Valuing individual apparatus events as regular events of weight 1 would best suit both the male and female teams' success against their competitors. Weighing the team all-around as 3 points is viable because not only do both the men's and women's USA have the potential to win based on this simulation, but there is less reliance on a single athlete.

### **Objective 3: All-Around vs Event Specialist vs Mixture (Women: Even Specialist, Men: Mixture)**

In our metric of success, we chose the total count of gold medals and we decided to weigh team all-around events as greater than individual all-around events and individual all-around great than the individual apparatuses. For the women's team, we believe it is best to select a team of five female athletes who are event-specialist gymnasts. The US women's team has a strong shot at winning the individual all-around and many individual apparatus events with multiple-apparatus specialist as well as win team all-around with highly decorated gold medalists who specialize in their apparatus, so focusing on athletes that specialize in apparatuses would be the best strategy (Appendix: Image 10). For the men's team, we believe it is best to select a team of five male athletes who are all-around gymnasts. The top male competitors for each apparatus from Team USA are almost always severely overshadowed by top male competitors from other countries by number of gold medal count. However, in vault the US makes up 7 of the top 10 most decorated gold medalists in the apparatus, so including as vault specialist could help the US men's gymnastics team increase chances of success. (Appendix: Image 12)

### **Objective 4: Identifying 5 Athletes**

Considering the conclusions of the previous objectives, we predict that the following athletes would best optimize gold medal count success for both the male and female US gymnastics team in the 2024 Paris Summer Olympics:

#### **Women's USA Gymnastics Team: Event Specialists Preference**

Our Team USA women's selection includes: Simone Biles, Shilese Jones, Zoe Miller, Konnor McClain, and Jade Carey.

In our results, we saw that Simone Biles was a strong individual apparatus (particularly in floor exercise, vault, and balance beam), individual all-around, and team all-around top-finisher contender—she is both a specialist and a generalist. To supplement Biles's performance and add strength to the US uneven bars performance, we choose Shilese Jones and Zoe Miller for their strong uneven bars rankings as specialists in the event. Furthermore, we choose Konnor McClain as a specialist in balance beam, as she has more simulated gold medals than does Simone Biles, but she may also compete on vault given fifth overall simulated ranking in vault total medals and fourth overall simulated ranking in vault gold medals. Lastly, Jade Carey we choose as another vault specialist given her third overall simulated ranking in vault, but she may also compete in floor exercise given her sixth overall simulated medal ranking in floor exercise. This selection provides two of the strongest USA specialists by medal count for almost each apparatus besides floor exercise since Simone received a whopping count of 192 gold medals in comparison the second place Brazilian contender with 58 gold medals in the simulation (Appendix: Image 9).

## **Men's USA Gymnastics Team: Mixture of Specialist and All-Around, All-Around Preference**

Our Team USA men's selection includes: Asher Hong, Curran Phillips, Donnell Whittenburg, Colt Walker, and Brody Malone.

In order to find the expected best all-around male athletes from the simulation, we gave rankings of total count of gold medals for each apparatus, took the average of those rankings for each athlete and picked the top five athletes with the highest average ranking (Appendix: Image 13). This method also matches our simulation results, which shows these five athletes (except for Asher Hong as a vault specialist, yet Asher can also rank high in all-around male athletes) as all-around gymnasts who can place in the top 10 of simulated total medals in at least two apparatuses, and cover all the apparatuses except for pommel horse.

## **Methodology and Data Evaluation**

The baseline choices in the methodology: taking a Bayesian approach and relying on the Monte Carlo method, allow for generally informed predictions (Yang, et. al 2022, Hoff 2008). However, there are areas where the implementation could be improved. The normal distribution is a simple choice for the posterior, but is not a perfect fit for the data. The normal distribution is unbounded, while gymnastics scores are bounded between 0 and 20. This discrepancy is addressed imperfectly through truncation, while a beta distribution could potentially be a better fit. Furthermore, when determining the prior parameters we use the mean and standard deviation of athlete results in a given apparatus, not accounting for the difference in sample count between athletes. We use a single distribution to model final scores, when we should be sampling from a distribution of difficulty scores, then conditioning on difficulty to sample execution and penalty scores to get a final score. This would allow us to incorporate the fact that difficulty and execution scores are not independent. Additionally, the simulated competitions include every gymnast in a single round, unlike the actual Olympics. Ideally, we'd simulate the multiple individual and team rounds in a gymnastics competition. The choice to avoid this modelling process, alongside the choice to only run 500 simulations, were done due to computational constraints. Finally, we assume that the athletes' abilities are constant over time, which is not necessarily true. This assumption is mildly addressed by using the most recent data, but it is still a simplification.

We run our model on a subsetting group of observations from 2022-2023 gymnastics competition data; it is likely that this subset is not representative of every athletes' true performances. We had to remove data for athletes' scores when the athlete did not compete in more than 2 competitions for an apparatus, which may have excluded some injured or upcoming athletes. Finally, given there are a limited number of international competitions per season, most athletes in the data set were competing in less than ten competitions. The limited number of score results per athlete may lead to hard to generalize results.

## **Implications and Conclusions**

A development of this study would be benefited if it addressed the methodological limitations mentioned above. Additionally, including more historical data and athletes' age in the model would create a much more robust model. The current methodology also lacks a selection mechanism, relying on us to manually select the top five athletes. Another change that would have advanced the specificity in the vault apparatus scores within our simulations would have been handling vault 1 and vault 2 as separate entities. Within individual apparatus events, two different vaults are required in the qualification and final event but in our simulation we used the mean of both vault events instead. Another change in our methodology would be to run more competition simulations to reduce variance. Overall, this study provides valuable insights on an optimal team selection strategy that would best aid the United States artistic gymnastics male and female team achieve success in the 2024 Paris Summer Olympics Games.



# Appendix

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## Data Discussion: Tokyo Olympics

Additionally, in the context of Olympic gymnastics, athletes of age 16 and older are eligible to compete but gymnastics is a sport in which most athletes retire in their early to mid-twenties. Specifically in the summer 2020 Tokyo Olympics only three female athletes aged 27 or older qualified to compete (Camenker, 2021). Furthermore, the average age for female gymnasts in the 2020 Olympics was approximately 22 years of age, meaning we assume that many of the competitors in the older data set will not be competing in the 2024 Paris Summer Olympics (Meyers, 2021).

## Data Cleaning Semantics and Justification

There were several cases of missing or inconsistent athlete first and last names, so we created unique athlete IDs using string methods by using the first three letters of an athlete’s first name, the first three letters of an athlete’s last name, and the country code. We also manually inserted missing names and accounted for names with less than three characters. Furthermore, the apparatus code for high bar was inconsistent across the Commonwealth Games and all other competitions, so we made sure to consolidate high bar into one apparatus code. Because individual apparatus qualifying vaults needed athletes to compete in two different vaults (VT1, VT2) as opposed to one vault in the finals or team or all-around events, we decided to take the higher of the two vault scores for an athlete for a competition, if there were two vaults completed, and consolidated that score as one vault apparatus code. We decided to keep the higher score given the vaults were different, and athletes likely compete with the vault that gives them the higher score during event finals.

## Additional Simulation Results

Given women compete on 4 apparatuses and men compete on 6 apparatuses, we have tables of the simulation outcomes for all 10 apparatuses.

Table 3: Women’s Balance Beam Simulation Results

Athlete & Country	Gold	Silver	Bronze	Total Medals
Simone Biles: USA	49	71	50	170
Yaqin Zhou: CHN	68	49	42	159
Konnor McClain: USA	65	47	29	141
Qingying Zhang: CHN	54	32	41	127
Sunisa Lee: USA	31	35	24	90
Huan Luo: CHN	24	15	17	56
Yushan Ou: CHN	12	21	17	50
Urara Ashikawa: JPN	15	15	11	41
Rebeca Andrade: BRA	11	14	13	38
Skye Blakely: USA	10	12	16	38

Table 4: Women’s Vault Simulation Results

Athlete & Country	Gold	Silver	Bronze	Total Medals
Simone Biles: USA	151	94	83	328
Rebeca Andrade: BRA	103	79	63	245
Jade Carey: USA	61	78	60	199
Jordan Chiles: USA	28	34	43	105
Konnor McClain: USA	40	32	31	103
Shilese Jones: USA	22	38	39	99
Ondine Achampong: GBR	14	31	46	91
Joscelyn Roberson: USA	15	29	34	78
Shokyo Miyata: JPN	26	21	30	77
Tiana Sumanasekera: USA	18	31	26	75

Table 5: Women’s Uneven Bars Simulation Results

Athlete & Country	Gold	Silver	Bronze	Total Medals
Kayla Neymour: ALG	82	55	42	179
Qiyang Qiu: CHN	51	43	51	145
Shilese Jones: USA	32	40	36	108
Alice D’Amato: ITA	28	37	36	101
Xijing Tang: CHN	33	29	30	92
Xiaoyuan Wei: CHN	30	28	31	89
Zoe Miller: USA	35	29	24	88
Rebeca Andrade: BRA	22	19	21	62
Elisabeth Seitz: GER	17	17	23	57
Simone Biles: USA	15	16	21	52

Table 6: Men’s Vault Simulation Results

Athlete & Country	Gold	Silver	Bronze	Total Medals
Jake Jarman: GBR	91	70	48	209
Asher Hong: USA	67	58	58	183
Daiki Hashimoto: JPN	55	55	46	156
Boheng Zhang: CHN	54	44	37	135
Khoe Young: USA	29	43	47	119
Curran Phillips: USA	33	42	37	112
Donnell Whittenburg: USA	35	38	38	111
Dallas Hale: USA	34	29	47	110
Colt Walker: USA	21	28	36	85
Taylor Burkhart: USA	25	27	27	79

Table 7: Men’s Floor Exercise Simulation Results

Athlete & Country	Gold	Silver	Bronze	Total Medals
Carlos Yulo: PHI	48	33	46	127
Ryosuke Doi: JPN	26	26	31	83
Artem Dolgopyat: ISR	21	22	26	69
Paul Juda: USA	28	21	13	62
Daiki Hashimoto: JPN	16	25	16	57
Boheng Zhang: CHN	19	18	12	49
Nicola Bartolini: ITA	13	18	12	43
Donnell Whittenburg: USA	16	18	9	43
Colt Walker: USA	16	13	12	41
Brody Malone: USA	11	14	15	40

Table 8: Men’s High Bar Simulation Results

Athlete & Country	Gold	Silver	Bronze	Total Medals
Daiki Hashimoto: JPN	44	45	35	124
Boheng Zhang: CHN	50	26	33	109
Cong Shi: CHN	35	38	27	100
Brody Malone: USA	18	29	25	72
Weide Su: CHN	23	20	16	59
Wei Sun: CHN	26	20	13	59
Shohei Kawakami: JPN	16	23	19	58
Ilias Georgiou: CYP	18	15	20	53
Milad Karimi: KAZ	25	11	15	51
Arthur Mariano: BRA	11	19	16	46

Table 9: Men’s Pommel Horse Simulation Results

Athlete & Country	Gold	Silver	Bronze	Total Medals
Max Whitlock: GBR	84	40	29	153
Chih Lee: TPE	57	45	27	129
Nariman Kurbanov: KAZ	31	52	35	118
Ahmad Abu Al Soud: JOR	15	26	25	66
Rhys McClenaghan: IRL	22	24	19	65
Stephen Nedoroscik: USA	20	15	18	53
Loran De Munck: NED	21	16	13	50
Gagik Khachikyan: ARM	7	18	22	47
Yu-Jan Shiao: TPE	11	16	18	45
Kakeru Tanigawa: JPN	11	12	21	44

Table 10: Men’s Still Rings Simulation Results

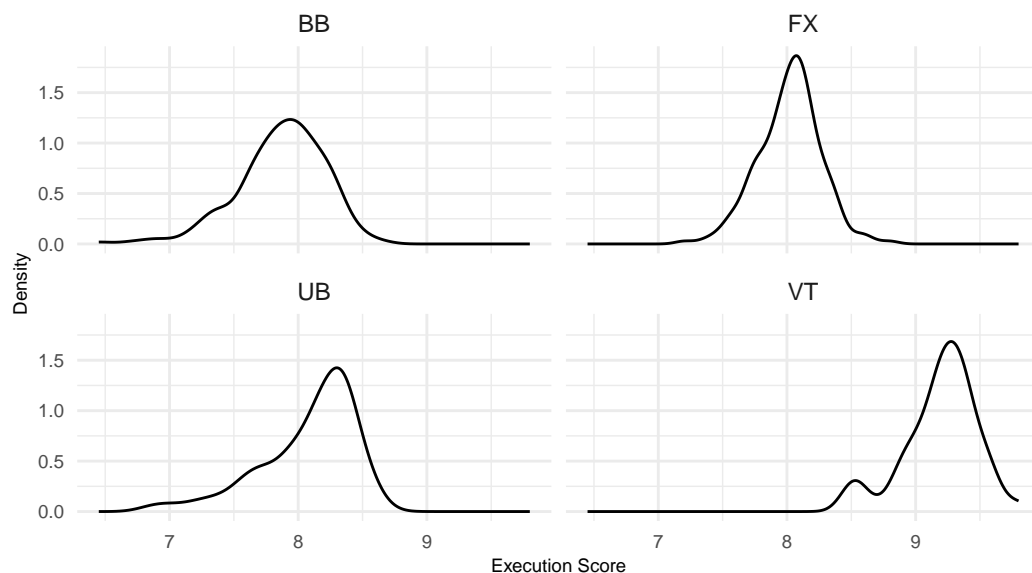
Athlete & Country	Gold	Silver	Bronze	Total Medals
Yang Liu: CHN	69	57	40	166
Xingyu Lan: CHN	41	47	29	117
Eleftherios Petrounias: GRE	38	34	36	108
Jingyuan Zou: CHN	44	25	23	92
Hao You: CHN	18	19	24	61
Ibrahim Colak: TUR	18	22	18	58
Donnell Whittenburg: USA	16	12	28	56
Adem Asil: TUR	10	17	22	49
Salvatore Maresca: ITA	12	24	13	49
Boheng Zhang: CHN	17	19	9	45

## Extra Visualizations

The following visualizations show the distribution of difficulty and execution scores by apparatus for male and female gymnasts, which are still approximately normal but do show more drastic deviations from normality than do the overall scores for each gymnast at an apparatus in a competition round. So, we thought it would be more fitting to fit normal-inverse gamma priors on the means and variances of the overall scores.

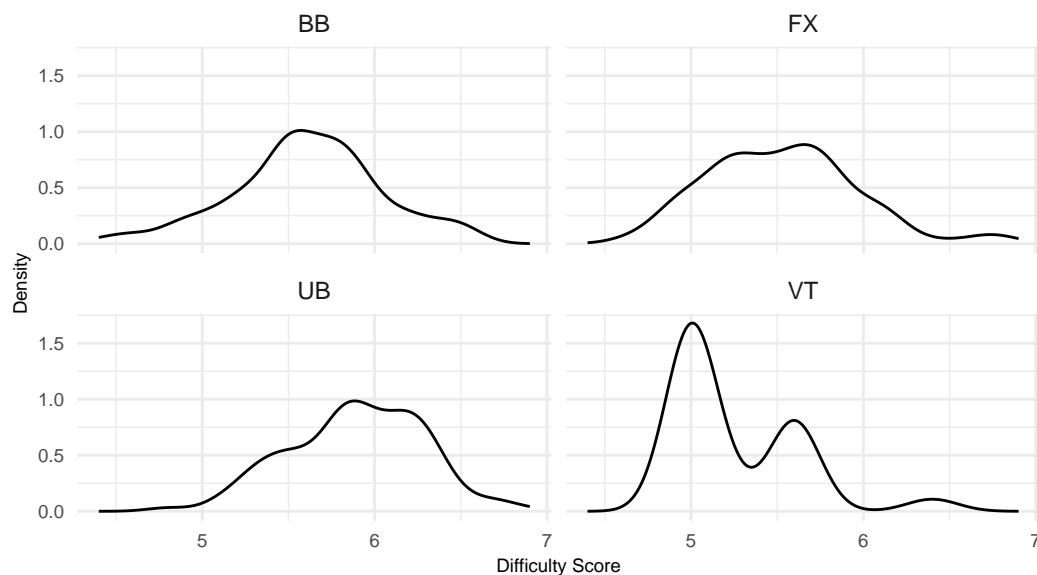
Distribution of Female Gymnasts' Execution Scores

By Apparatus



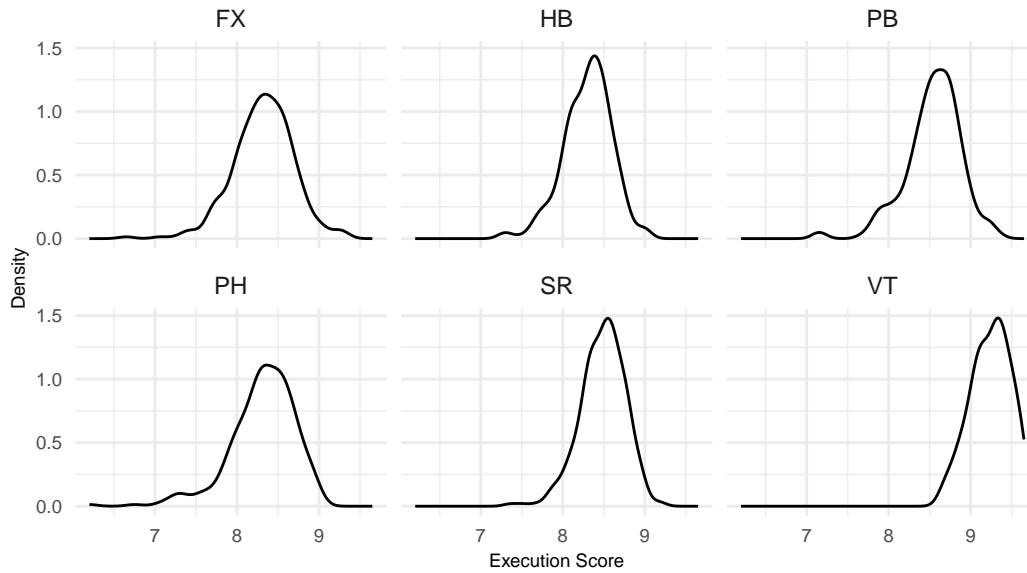
Distribution of Female Gymnasts' Difficulty Scores

By Apparatus



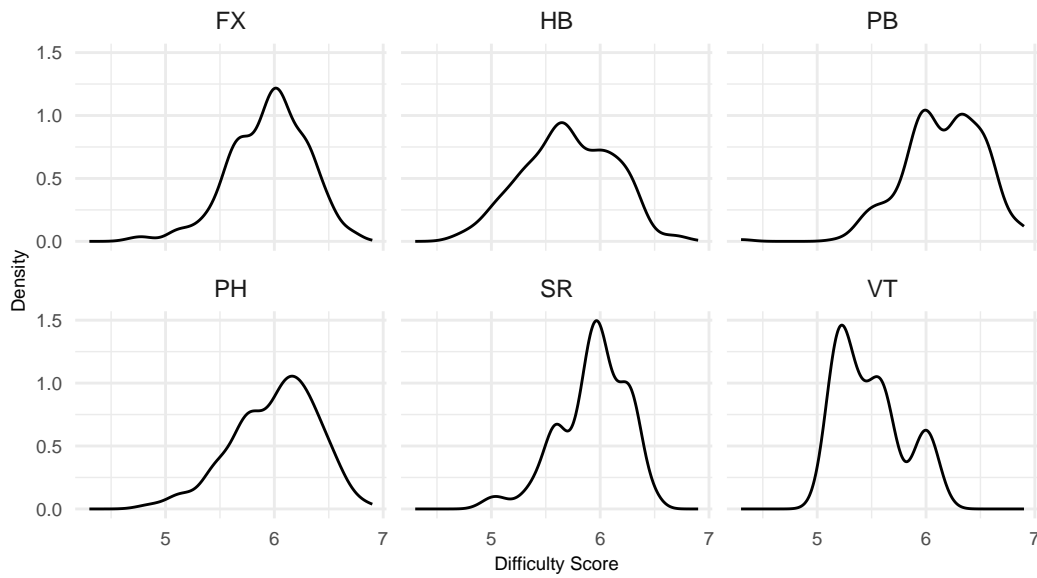
### Distribution of Male Gymnasts' Execution Scores

By Apparatus



### Distribution of Male Gymnasts' Difficulty Scores

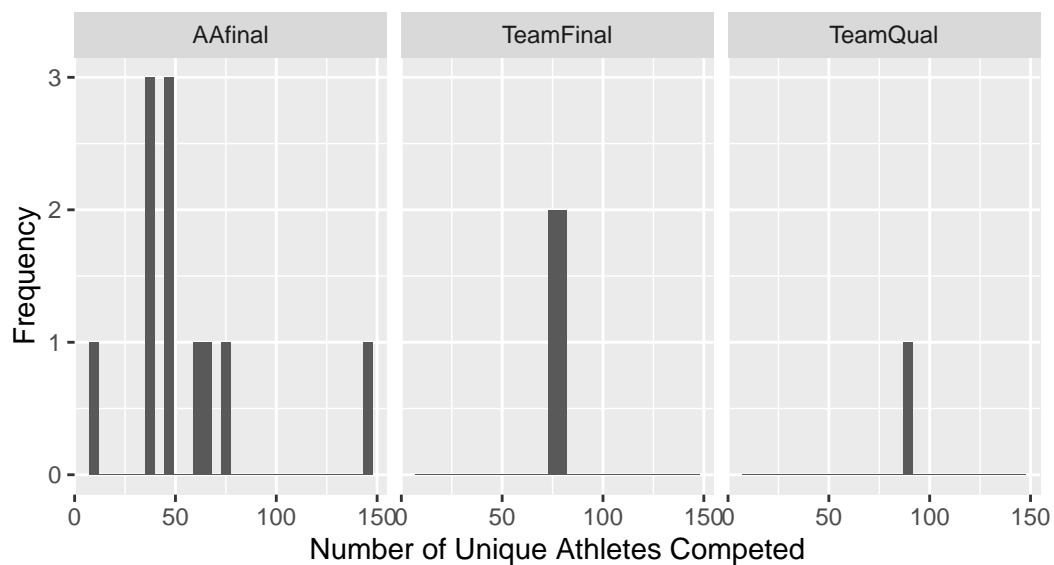
By Apparatus



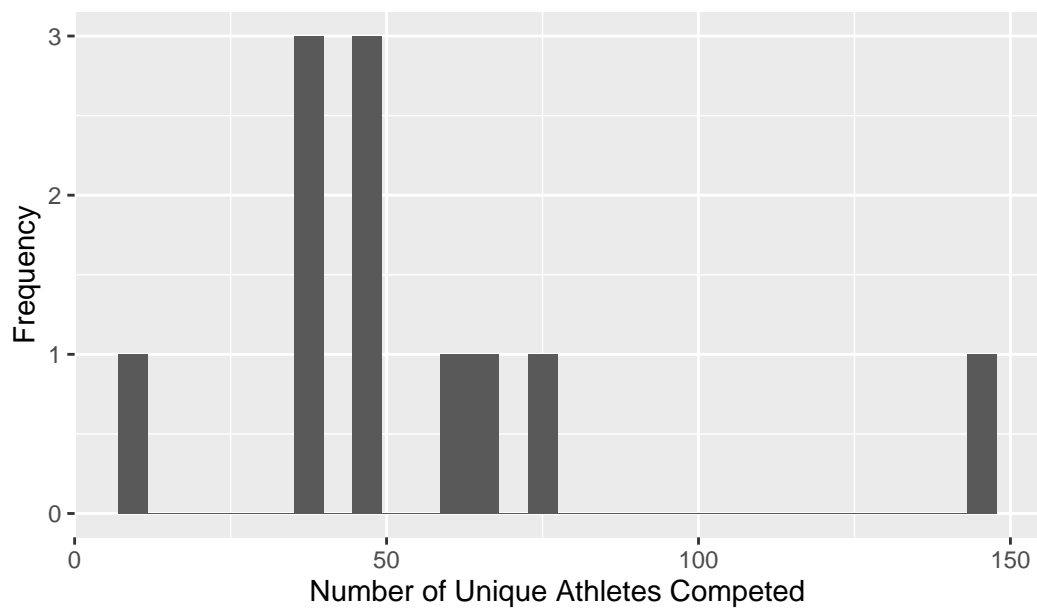
The below plots visualize how many unique athletes are competing at each round in a competition, spearated by gender, so that we can understand sample size for when we filter out data.

## 1) Distribution of Athletes Competed at Competition Rounds

All Around or Team All Arouns

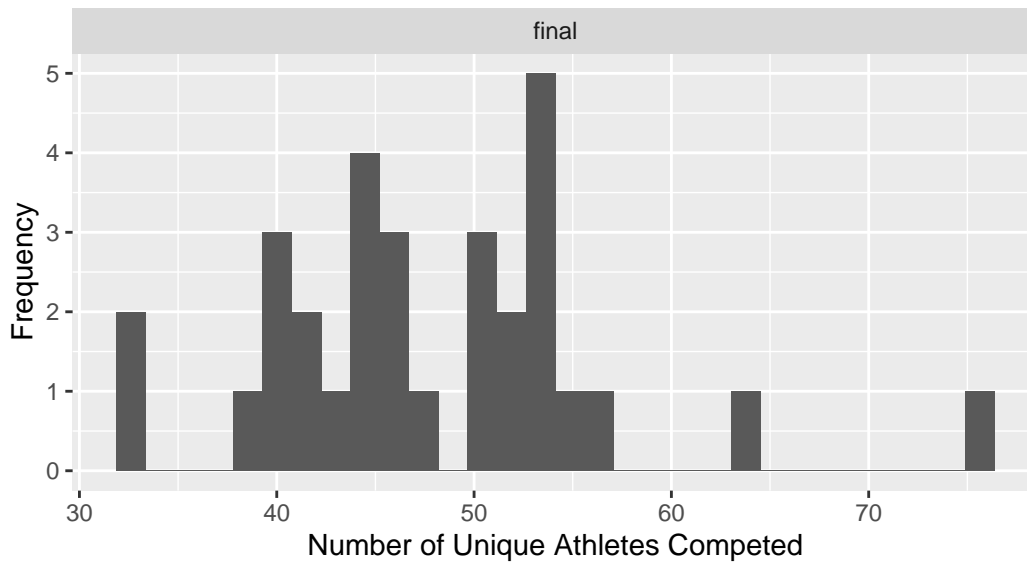


## 2) Distribution of Athletes Competed at AA Finals

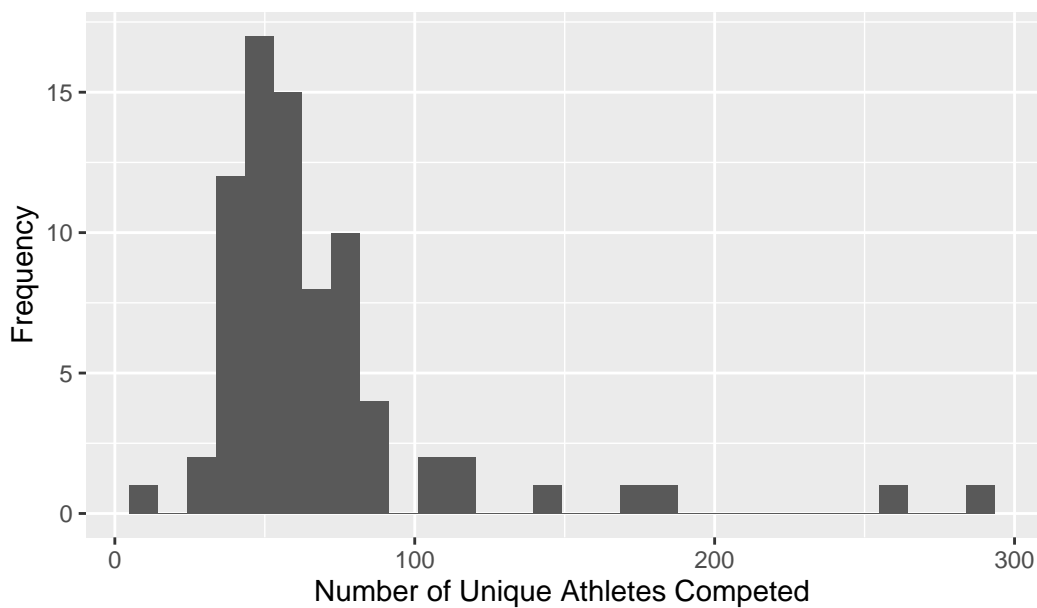


### 3) Distribution of Athletes Competed at Final Rounds

#### Individual Apparatuses



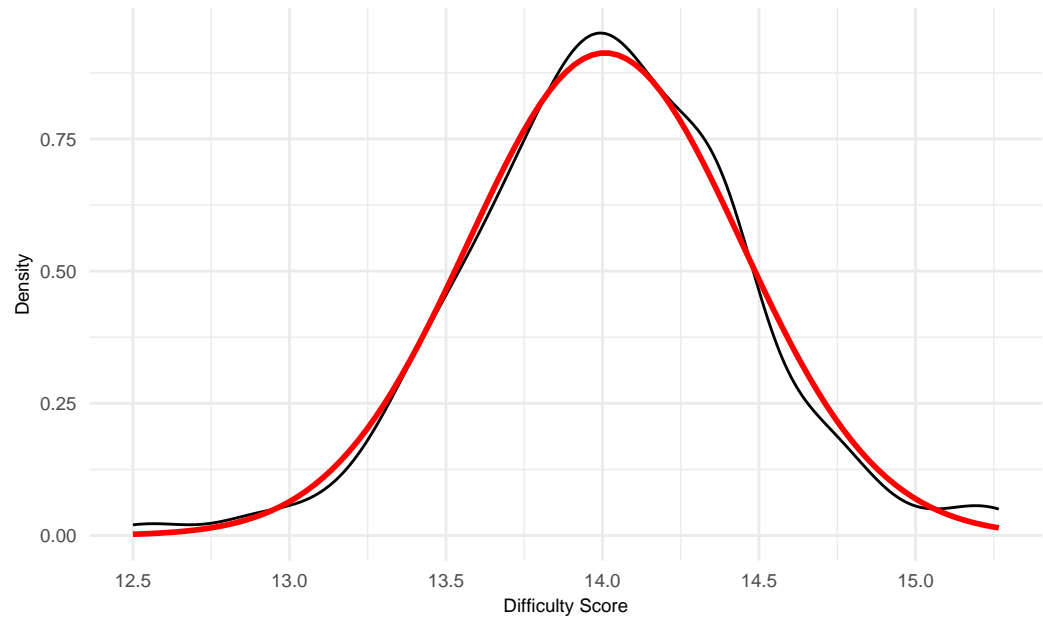
### 4) Distribution of Athletes Competed at Competitions



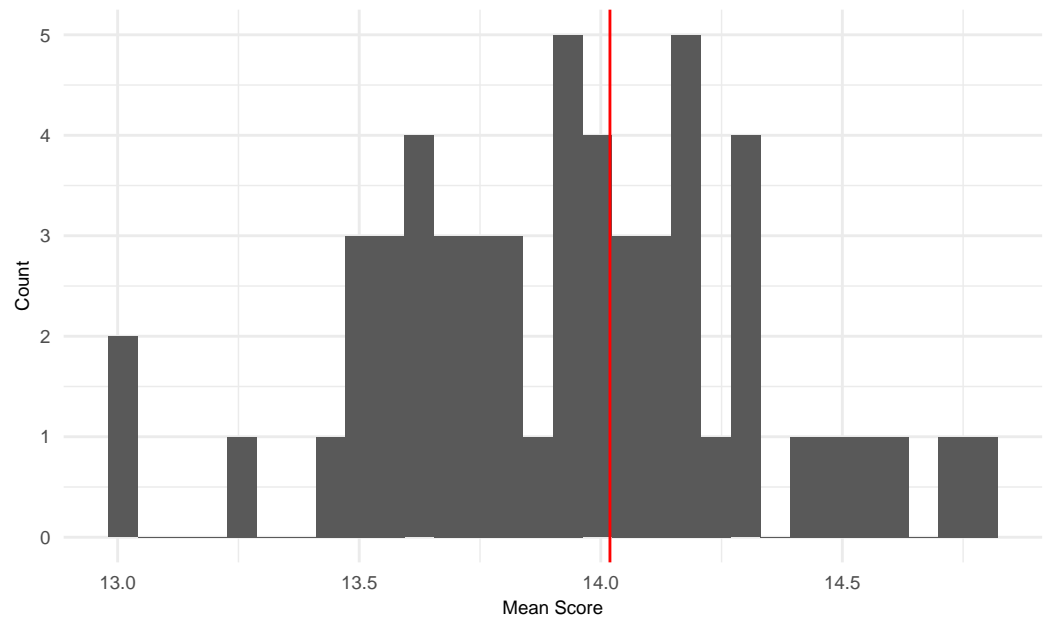
### Posterior Predictive Checks

Additionally, we look at the distribution of mean scores and the distribution of variance scores for men's high bar apparatus as an example of how we will fit normal-inverse gamma priors for the means and variances. We can see that the distribution of mean scores follows an approximately normal distribution and the distribution of variance scores follow an approximately inverse-gamma distribution.

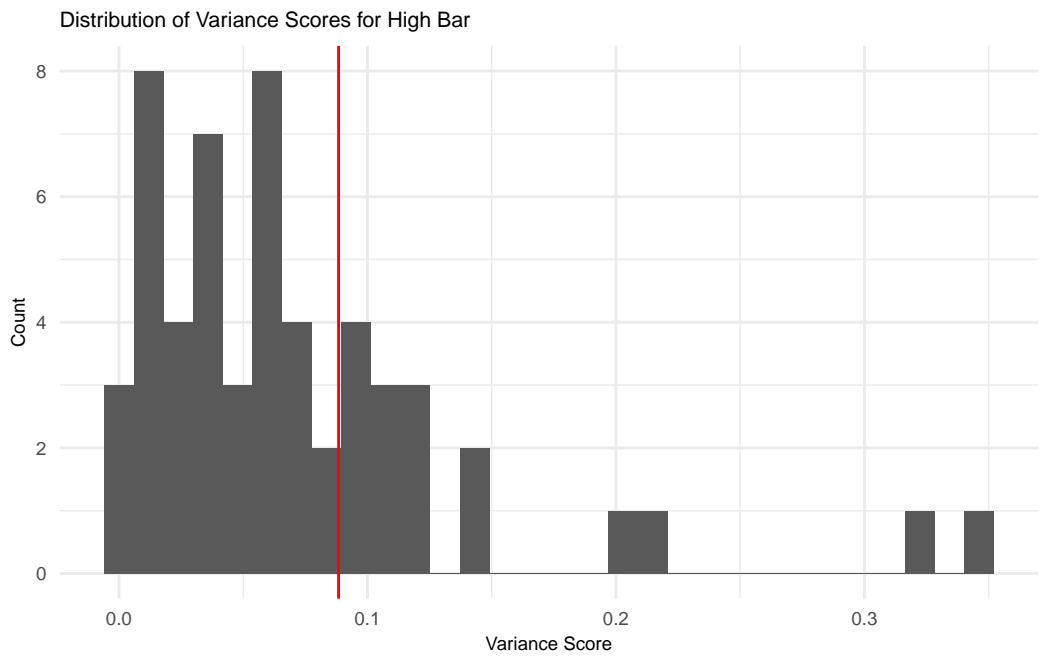
High Bar Score Distribution Compared to Fitted Normal Distribution



Distribution of Mean Scores for High Bar

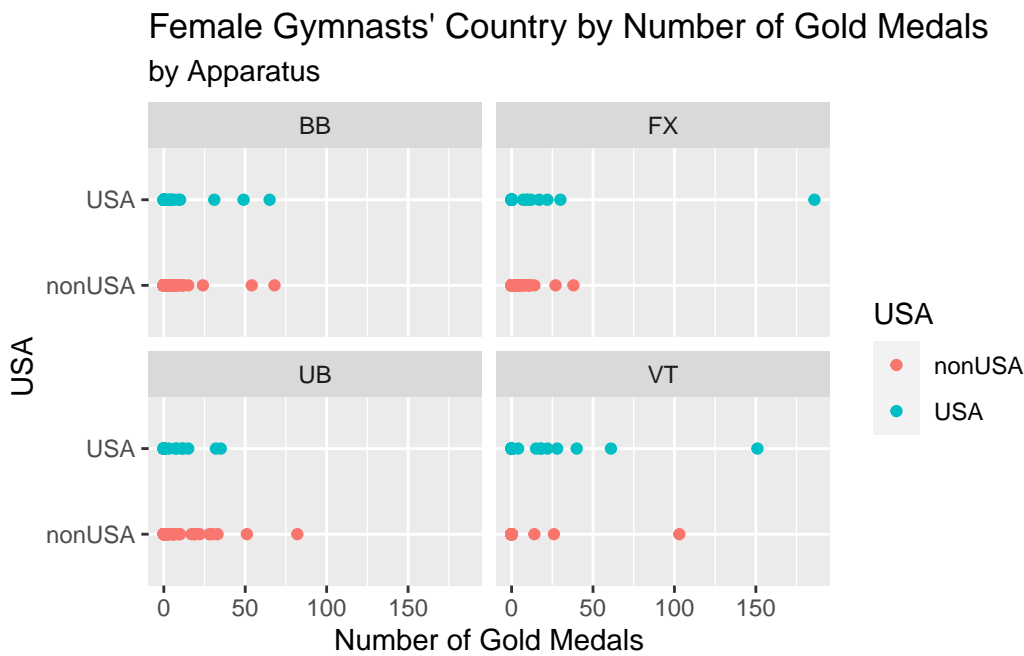




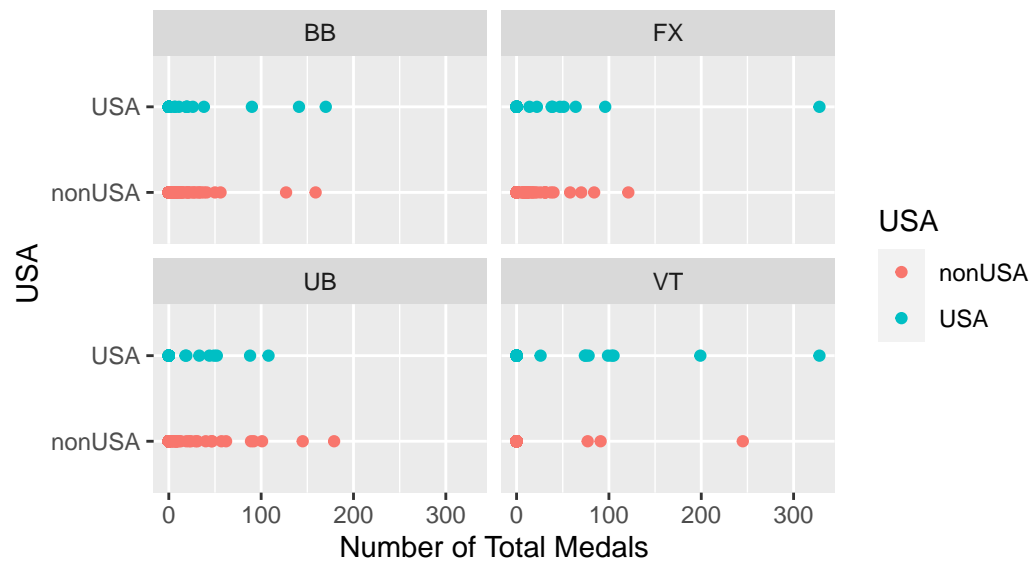


Comparing Simulation Results

Image 5)



Female Gymnasts' Country by Number of Total Medals  
by Apparatus



Female Gymnasts' Country by Medal Weight  
by Apparatus

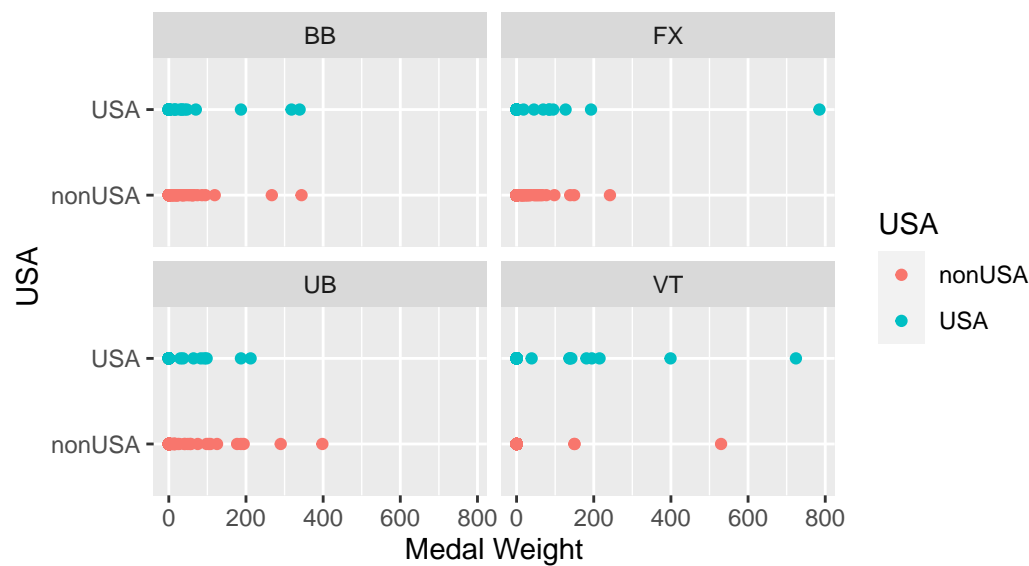
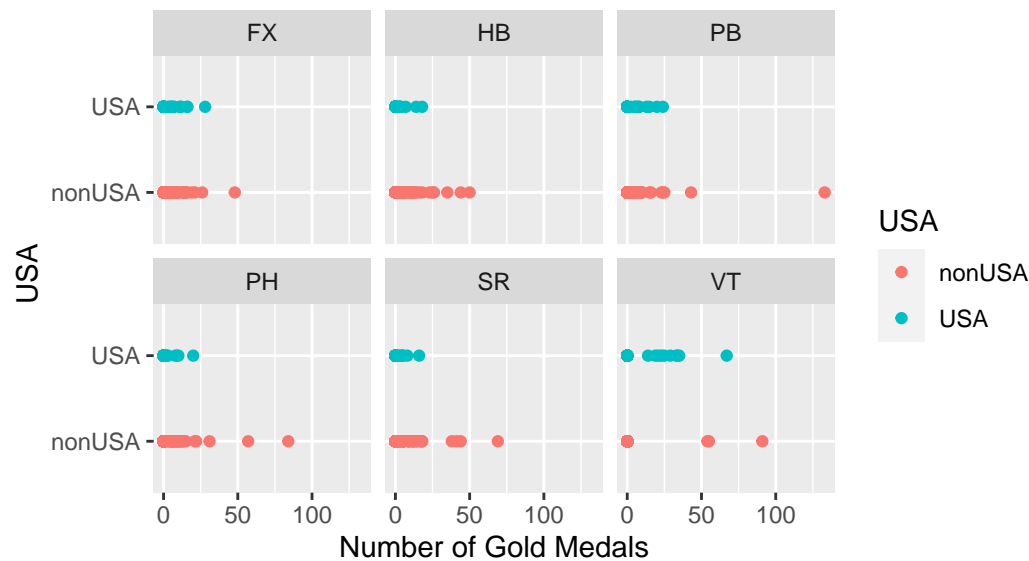
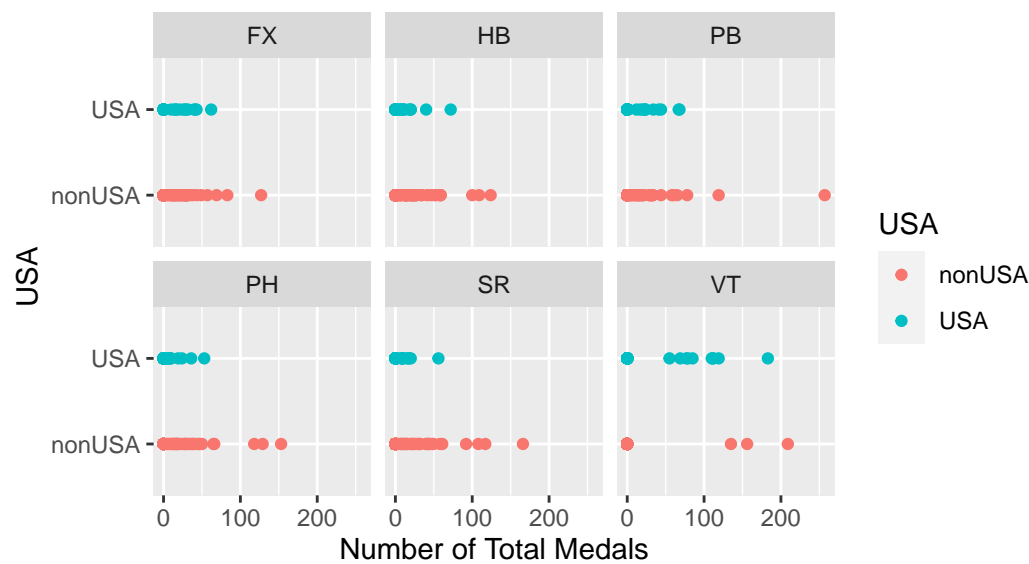


Image 6)

Male Gymnasts' Country by Number of Gold Medals  
by Apparatus



Male Gymnasts' Country by Number of Total Medals  
by Apparatus



Male Gymnasts' Country by Medal Weight  
by Apparatus

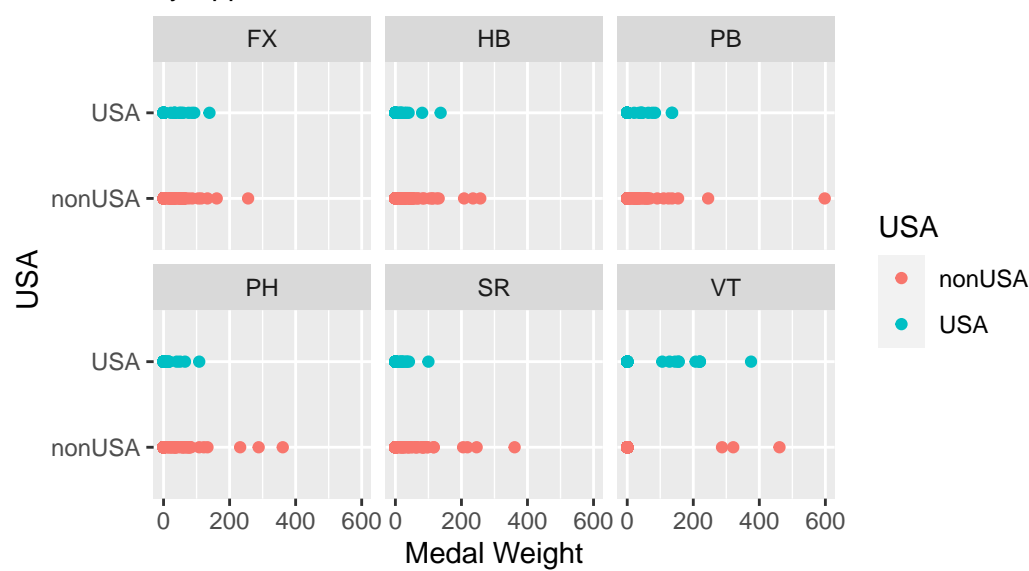


Image 7)

Women:

- Top 5 athletes by apparatus for each of the 3 success metrics
- Sum of each of the 3 metrics made by athletes from the US and non-US countries

Table 11: Top Women's Athletes by Gold Medal Count

Athlete & Country	Golds	Silvers	Bronzes	Total Medals	Country	Medal Weight	Apparatus	Status
Yaqin Zhou: CHN	68	49	42	159	CHN	344	BB	nonUSA
Konnor McClain: USA	65	47	29	141	USA	318	BB	USA
Qingying Zhang: CHN	54	32	41	127	CHN	267	BB	nonUSA
Simone Biles: USA	49	71	50	170	USA	339	BB	USA
Sunisa Lee: USA	31	35	24	90	USA	187	BB	USA
Simone Biles: USA	186	85	57	328	USA	785	FX	USA
Rebeca Andrade: BRA	38	45	38	121	BRA	242	FX	nonUSA
Kaliya Lincoln: USA	30	37	29	96	USA	193	FX	USA
Flavia Saraiva: BRA	27	25	18	70	BRA	149	FX	nonUSA
Jade Carey: USA	22	19	23	64	USA	127	FX	USA
Kayla Neymour: ALG	82	55	42	179	ALG	398	UB	nonUSA
Qiyan Qiu: CHN	51	43	51	145	CHN	290	UB	nonUSA
Zoe Miller: USA	35	29	24	88	USA	187	UB	USA
Xijing Tang: CHN	33	29	30	92	CHN	187	UB	nonUSA
Shilese Jones: USA	32	40	36	108	USA	212	UB	USA
Simone Biles: USA	151	94	83	328	USA	724	VT	USA
Rebeca Andrade: BRA	103	79	63	245	BRA	530	VT	nonUSA
Jade Carey: USA	61	78	60	199	USA	399	VT	USA
Konnor McClain: USA	40	32	31	103	USA	215	VT	USA
Jordan Chiles: USA	28	34	43	105	USA	195	VT	USA

Table 12: Top Women’s Athletes by Total Medal Count

Athlete & Country	Gold	Silver	Bronze	Total Medals	Country	Medal Weight	Apparatus	Status
Simone Biles: USA	49	71	50	170	USA	339	BB	USA
Yaqin Zhou: CHN	68	49	42	159	CHN	344	BB	nonUSA
Konnor McClain: USA	65	47	29	141	USA	318	BB	USA
Qingying Zhang: CHN	54	32	41	127	CHN	267	BB	nonUSA
Sunisa Lee: USA	31	35	24	90	USA	187	BB	USA
Simone Biles: USA	186	85	57	328	USA	785	FX	USA
Rebeca Andrade: BRA	38	45	38	121	BRA	242	FX	nonUSA
Kaliya Lincoln: USA	30	37	29	96	USA	193	FX	USA
Jessica Gadirova: GBR	14	27	43	84	GBR	139	FX	nonUSA
Flavia Saraiva: BRA	27	25	18	70	BRA	149	FX	nonUSA
Kayla Neymour: ALG	82	55	42	179	ALG	398	UB	nonUSA
Qiyan Qiu: CHN	51	43	51	145	CHN	290	UB	nonUSA
Shilese Jones: USA	32	40	36	108	USA	212	UB	USA
Alice D’Amato: ITA	28	37	36	101	ITA	194	UB	nonUSA
Xijing Tang: CHN	33	29	30	92	CHN	187	UB	nonUSA
Simone Biles: USA	151	94	83	328	USA	724	VT	USA
Rebeca Andrade: BRA	103	79	63	245	BRA	530	VT	nonUSA
Jade Carey: USA	61	78	60	199	USA	399	VT	USA
Jordan Chiles: USA	28	34	43	105	USA	195	VT	USA
Konnor McClain: USA	40	32	31	103	USA	215	VT	USA

Table 13: Top Women’s Athletes by Weighted Medal Count

Athlete & Country	Gold	Silver	Bronze	Total Medals	Country	Medal Weight	Apparatus	Status
Yaqin Zhou: CHN	68	49	42	159	CHN	344	BB	nonUSA
Simone Biles: USA	49	71	50	170	USA	339	BB	USA
Konnor McClain: USA	65	47	29	141	USA	318	BB	USA
Qingying Zhang: CHN	54	32	41	127	CHN	267	BB	nonUSA
Sunisa Lee: USA	31	35	24	90	USA	187	BB	USA
Simone Biles: USA	186	85	57	328	USA	785	FX	USA
Rebeca Andrade: BRA	38	45	38	121	BRA	242	FX	nonUSA
Kaliya Lincoln: USA	30	37	29	96	USA	193	FX	USA
Flavia Saraiva: BRA	27	25	18	70	BRA	149	FX	nonUSA
Jessica Gadirova: GBR	14	27	43	84	GBR	139	FX	nonUSA
Kayla Neymour: ALG	82	55	42	179	ALG	398	UB	nonUSA
Qiyan Qiu: CHN	51	43	51	145	CHN	290	UB	nonUSA
Shilese Jones: USA	32	40	36	108	USA	212	UB	USA
Alice D’Amato: ITA	28	37	36	101	ITA	194	UB	nonUSA
Xijing Tang: CHN	33	29	30	92	CHN	187	UB	nonUSA
Zoe Miller: USA	35	29	24	88	USA	187	UB	USA
Simone Biles: USA	151	94	83	328	USA	724	VT	USA
Rebeca Andrade: BRA	103	79	63	245	BRA	530	VT	nonUSA
Jade Carey: USA	61	78	60	199	USA	399	VT	USA
Konnor McClain: USA	40	32	31	103	USA	215	VT	USA
Jordan Chiles: USA	28	34	43	105	USA	195	VT	USA

Table 14: US Women’s Medal Proportion Per Medal Metric

Status	Sum Total Golds	Sum Total Medals	Sum Weighted Medals
nonUSA	1040	3236	6380
USA	960	2764	5620

For the women’s simulation when looking at the top 5 athletes by:

- *Gold Medal Count* for each apparatus there are 10 out of 20 from the US: balance beam (BB): 3, floor exercise (FX): 3, uneven bars (UB): 2, and vault (VT): 2
  - USA makes up 51% of the total women’s gold medals in the simulation.
- *Total Medal Count* for each apparatus there are 12 out of 20 from the US: balance beam (BB): 3, floor exercise (FX): 4, uneven bars (UB): 1, vault (VT): 4

– USA makes up 47% of the total women’s medals in the simulation.

- *Weighted Medal Count* for each apparatus there are 10 out of 20 from the US: balance beam (BB): 3, floor exercise (FX): 2, uneven bars (UB): 1, vault (VT): 4

– USA makes up 48% of the weight of women’s medals in the simulation.

## Image 8)

Men:

- Top 5 athletes by apparatus for each of the 3 success metrics
- Sum of each of the 3 metrics made by athletes from the US and non-US countries

Table 15: Top Men’s Athletes by Gold Medal Count

Athlete & Country	Golds	Silvers	Bronzes	Total Medals	Country	Medal Weight	Apparatus	Status
Carlos Yulo: PHI	48	33	46	127	PHI	256	FX	nonUSA
Paul Juda: USA	28	21	13	62	USA	139	FX	USA
Ryosuke Doi: JPN	26	26	31	83	JPN	161	FX	nonUSA
Artem Dolgopyat: ISR	21	22	26	69	ISR	133	FX	nonUSA
Boheng Zhang: CHN	19	18	12	49	CHN	105	FX	nonUSA
Boheng Zhang: CHN	50	26	33	109	CHN	235	HB	nonUSA
Daiki Hashimoto: JPN	44	45	35	124	JPN	257	HB	nonUSA
Cong Shi: CHN	35	38	27	100	CHN	208	HB	nonUSA
Wei Sun: CHN	26	20	13	59	CHN	131	HB	nonUSA
Milad Karimi: KAZ	25	11	15	51	KAZ	112	HB	nonUSA
Jingyuan Zou: CHN	133	75	49	257	CHN	598	PB	nonUSA
Lukas Dauser: GER	43	40	36	119	GER	245	PB	nonUSA
Boheng Zhang: CHN	25	26	27	78	CHN	154	PB	nonUSA
Curran Phillips: USA	24	20	24	68	USA	136	PB	USA
Joe Fraser: GBR	24	17	19	60	GBR	125	PB	nonUSA
Max Whitlock: GBR	84	40	29	153	GBR	361	PH	nonUSA
Chih Lee: TPE	57	45	27	129	TPE	288	PH	nonUSA
Nariman Kurbanov: KAZ	31	52	35	118	KAZ	232	PH	nonUSA
Rhys McClenaghan: IRL	22	24	19	65	IRL	133	PH	nonUSA
Loran De Munck: NED	21	16	13	50	NED	108	PH	nonUSA
Yang Liu: CHN	69	57	40	166	CHN	361	SR	nonUSA
Jingyuan Zou: CHN	44	25	23	92	CHN	205	SR	nonUSA
Xingyu Lan: CHN	41	47	29	117	CHN	246	SR	nonUSA
Eleftherios Petrounias: GRE	38	34	36	108	GRE	218	SR	nonUSA
Hao You: CHN	18	19	24	61	CHN	116	SR	nonUSA
Ibrahim Colak: TUR	18	22	18	58	TUR	116	SR	nonUSA
Jake Jarman: GBR	91	70	48	209	GBR	461	VT	nonUSA
Asher Hong: USA	67	58	58	183	USA	375	VT	USA
Daiki Hashimoto: JPN	55	55	46	156	JPN	321	VT	nonUSA
Boheng Zhang: CHN	54	44	37	135	CHN	287	VT	nonUSA
Donnell Whittenburg: USA	35	38	38	111	USA	219	VT	USA

Table 16: Top Men's Athletes by Total Medal Count

Athlete & Country	Golds	Silvers	Bronzes	Total Medals	Country	Medal Weight	Apparatus	Status
Carlos Yulo: PHI	48	33	46	127	PHI	256	FX	nonUSA
Ryosuke Doi: JPN	26	26	31	83	JPN	161	FX	nonUSA
Artem Dolgopyat: ISR	21	22	26	69	ISR	133	FX	nonUSA
Paul Juda: USA	28	21	13	62	USA	139	FX	USA
Daiki Hashimoto: JPN	16	25	16	57	JPN	114	FX	nonUSA
Daiki Hashimoto: JPN	44	45	35	124	JPN	257	HB	nonUSA
Boheng Zhang: CHN	50	26	33	109	CHN	235	HB	nonUSA
Cong Shi: CHN	35	38	27	100	CHN	208	HB	nonUSA
Brody Malone: USA	18	29	25	72	USA	137	HB	USA
Weide Su: CHN	23	20	16	59	CHN	125	HB	nonUSA
Wei Sun: CHN	26	20	13	59	CHN	131	HB	nonUSA
Jingyuan Zou: CHN	133	75	49	257	CHN	598	PB	nonUSA
Lukas Dauser: GER	43	40	36	119	GER	245	PB	nonUSA
Boheng Zhang: CHN	25	26	27	78	CHN	154	PB	nonUSA
Curran Phillips: USA	24	20	24	68	USA	136	PB	USA
Colt Walker: USA	20	28	19	67	USA	135	PB	USA
Max Whitlock: GBR	84	40	29	153	GBR	361	PH	nonUSA
Chih Lee: TPE	57	45	27	129	TPE	288	PH	nonUSA
Nariman Kurbanov: KAZ	31	52	35	118	KAZ	232	PH	nonUSA
Ahmad Abu Al Soud: JOR	15	26	25	66	JOR	122	PH	nonUSA
Rhys McClenaghan: IRL	22	24	19	65	IRL	133	PH	nonUSA
Yang Liu: CHN	69	57	40	166	CHN	361	SR	nonUSA
Xingyu Lan: CHN	41	47	29	117	CHN	246	SR	nonUSA
Eleftherious Petrounias: GRE	38	34	36	108	GRE	218	SR	nonUSA
Jingyuan Zou: CHN	44	25	23	92	CHN	205	SR	nonUSA
Hao You: CHN	18	19	24	61	CHN	116	SR	nonUSA
Jake Jarman: GBR	91	70	48	209	GBR	461	VT	nonUSA
Asher Hong: USA	67	58	58	183	USA	375	VT	USA
Daiki Hashimoto: JPN	55	55	46	156	JPN	321	VT	nonUSA
Boheng Zhang: CHN	54	44	37	135	CHN	287	VT	nonUSA
Khoi Young: USA	29	43	47	119	USA	220	VT	USA

Table 17: Top Men's Athletes by Weighted Medal Count

Athlete & Country	Golds	Silvers	Bronzes	Total Medals	Country	Medal Weight	Apparatus	Status
Carlos Yulo: PHI	48	33	46	127	PHI	256	FX	nonUSA
Ryosuke Doi: JPN	26	26	31	83	JPN	161	FX	nonUSA
Paul Juda: USA	28	21	13	62	USA	139	FX	USA
Artem Dolgopyat: ISR	21	22	26	69	ISR	133	FX	nonUSA
Daiki Hashimoto: JPN	16	25	16	57	JPN	114	FX	nonUSA
Daiki Hashimoto: JPN	44	45	35	124	JPN	257	HB	nonUSA
Boheng Zhang: CHN	50	26	33	109	CHN	235	HB	nonUSA
Cong Shi: CHN	35	38	27	100	CHN	208	HB	nonUSA
Brody Malone: USA	18	29	25	72	USA	137	HB	USA
Wei Sun: CHN	26	20	13	59	CHN	131	HB	nonUSA
Jingyuan Zou: CHN	133	75	49	257	CHN	598	PB	nonUSA
Lukas Dauser: GER	43	40	36	119	GER	245	PB	nonUSA
Boheng Zhang: CHN	25	26	27	78	CHN	154	PB	nonUSA
Curran Phillips: USA	24	20	24	68	USA	136	PB	USA
Kaito Sugimoto: JPN	23	25	17	65	JPN	136	PB	nonUSA
Max Whitlock: GBR	84	40	29	153	GBR	361	PH	nonUSA
Chih Lee: TPE	57	45	27	129	TPE	288	PH	nonUSA
Nariman Kurbanov: KAZ	31	52	35	118	KAZ	232	PH	nonUSA
Rhys McClenaghan: IRL	22	24	19	65	IRL	133	PH	nonUSA
Ahmad Abu Al Soud: JOR	15	26	25	66	JOR	122	PH	nonUSA
Yang Liu: CHN	69	57	40	166	CHN	361	SR	nonUSA
Xingyu Lan: CHN	41	47	29	117	CHN	246	SR	nonUSA
Eleftherios Petrounias: GRE	38	34	36	108	GRE	218	SR	nonUSA
Jingyuan Zou: CHN	44	25	23	92	CHN	205	SR	nonUSA
Hao You: CHN	18	19	24	61	CHN	116	SR	nonUSA
Ibrahim Colak: TUR	18	22	18	58	TUR	116	SR	nonUSA
Jake Jarman: GBR	91	70	48	209	GBR	461	VT	nonUSA
Asher Hong: USA	67	58	58	183	USA	375	VT	USA
Daiki Hashimoto: JPN	55	55	46	156	JPN	321	VT	nonUSA
Boheng Zhang: CHN	54	44	37	135	CHN	287	VT	nonUSA
Khoi Young: USA	29	43	47	119	USA	220	VT	USA
Curran Phillips: USA	33	42	37	112	USA	220	VT	USA

Table 18: US Men's Medal Proportion Per Medal Metric

Status	Sum Total Golds	Sum Total Medals	Sum Weighted Medals
nonUSA	2293	6667	13490
USA	707	2333	4510

For the men's simulation when looking at the top 5 athletes by:

- *Gold Medal Count* for each apparatus there are 5 out of 30 from the US: floor exercise (FX): 1, high bar (HB): 1, parallel bars (PB): 1 pommel horse (PH): 0, still rings (SR): 0, vault (VT): 2
  - USA makes up 21% of the total men's gold medals in the simulation.
- *Total Medal Count* for each apparatus there are 4 out of 30 from the US: floor exercise (FX): 1, high bar (HB): 1, parallel bars (PB): 0, pommel horse (PH): 0, still rings (SR): 0, vault (VT): 2
  - USA makes up 24% of the total men's medals in the simulation.
- *Weighted Medal Count* for each apparatus there are 4 out of 30 from the US: floor exercise (FX): 1, high bar (HB): 1, parallel bars (PB): 0, pommel horse (PH): 0, still rings (SR): 0, vault (VT): 2
  - USA makes up 23% of the weight of men's medals in the simulation.

**Image 9)**



### 9) Women: Country of Top 5 Athletes by Number of Gold Medals by Apparatus

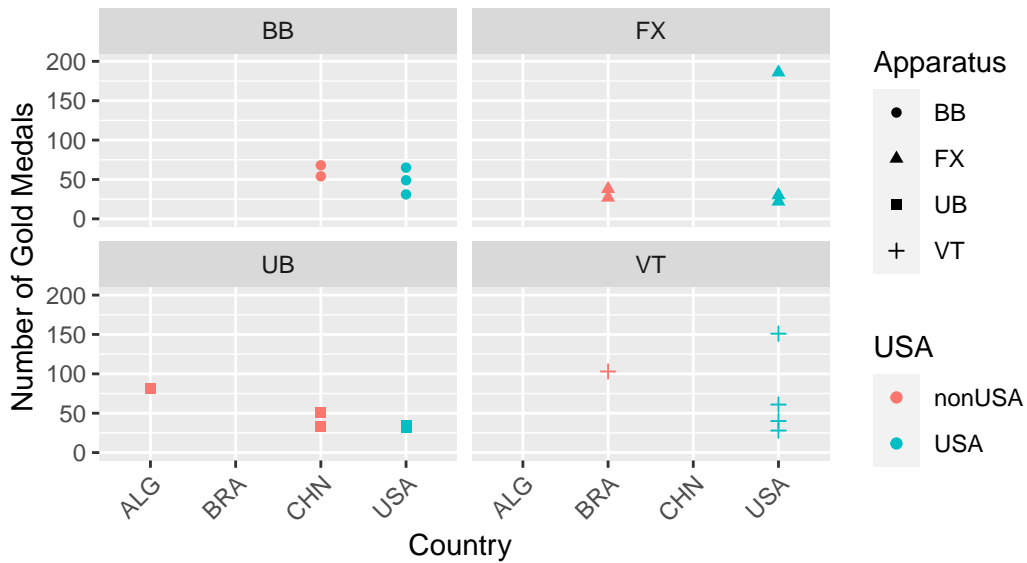
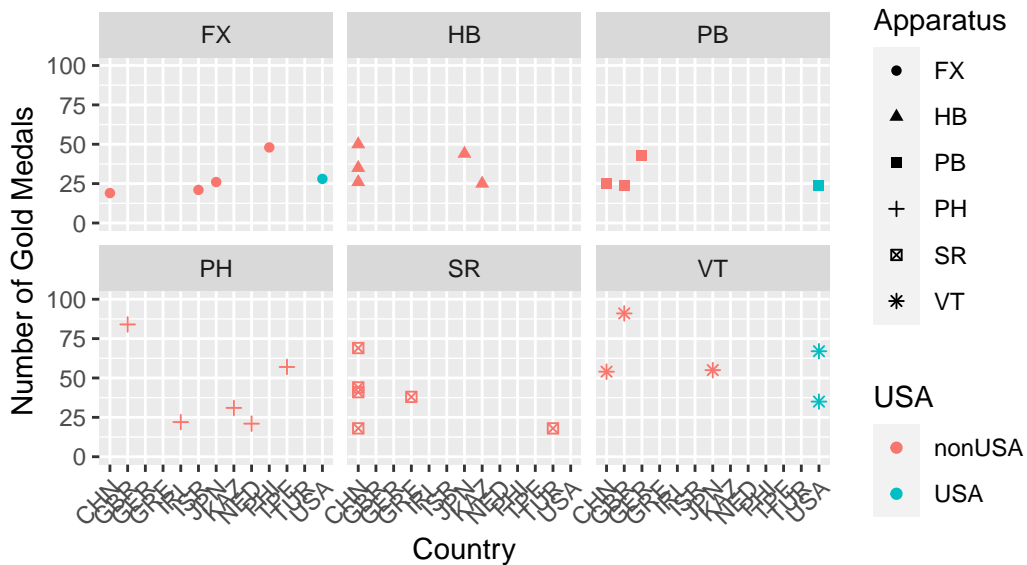


Image 10)

### 10) Men: Country of Top 5 Athletes by Number of Gold Medals by Apparatus



**Note:** The excessive number of countries display that there is not much overlap in the top 5 most gold medal decorated athletes on the men's team and therefore the lack of well-rounded gymnasts.

Image 11)

Average of total gold medal count ranking by apparatus of all US male gymnasts in ascending order (to find best all around gymnast for men's team)

Table 19: Average Overall Rank of USA Athletes By Number of Gold Medals (Top 6)

Athlete & Country	Average Rank
Donnell Whittenburg: USA	13.66667
Asher Hong: USA	14.00000
Brody Malone: USA	14.00000
Colt Walker: USA	14.33333
Paul Juda: USA	15.50000
Curran Phillips: USA	15.66667