# 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, during the qualifications round, from the 5 team members, 4 will compete on each apparatus, and the 3 highest scores will count and be summed. In the finals, the top 8 countries will qualify and compete in team all-around, where from the 5 team members, 3 will compete on each apparatus and all 3 scores will count. In the individual all-around finals, 24 athletes will qualify, with maximum 2 athletes per country. In the individual apparatus finals, 8 athletes will qualify per apparatus with a maximum of 2 athletes per country. The low number of athletes that qualify for the finals suggests there must be thoughtful crafting of the team of 5. 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 clean data sets of the accumulation of results of teams worldwide that participated in the major domestic and international gymnastic qualifying and final competition events leading up to the 2024 Summer Olympic Games. The first data set includes includes the results of the 2020 (taking place in 2021) Tokyo Summer Olympics qualifying and final rounds, and the second data set includes competitions in the 2022 and 2023 seasons. Observations for both data sets are at the athlete- and apparatus-level score for an event in a round at a gymnastics competition–for example, Simone Biles's final uneven bars score at the 2023 US Gymnastics Championships. It is worth noting, however, that the data from the 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. The data are collected from the results on each corresponding competition's official website, which are results from the officially judged scores of each competition. Variables in the data sets include first and last names of each athlete, gender, country, date of competition, name of competition, the round of the competition (e.g. qualifier or final of an individual apparatus, individual all-around, or team event), the location of the competition, apparatus (women compete in "BB": balance beam, "FX": floor exercise, "UB": uneven bars, and "VT": vault; men compete in "FX": floor exercise, HB": high bar, "PB": parallel bars, "PH": pommel horse, "SR": still rings, "VT": vault; beyond the floor and vault overlap, both men and women may compete in vaults "VT1" and "VT2", which are 2 different vaults required in individual apparatus qualifications and finals), the execution score, difficulty score, penalty, and final score for that athlete on that apparatus, and the rank of that athlete in that apparatus and round.

We decided to not proceed in using the data set of results from the Tokyo Summer Olympics since the data consisted only of female athletes and one competition (the Olympic Games). 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).

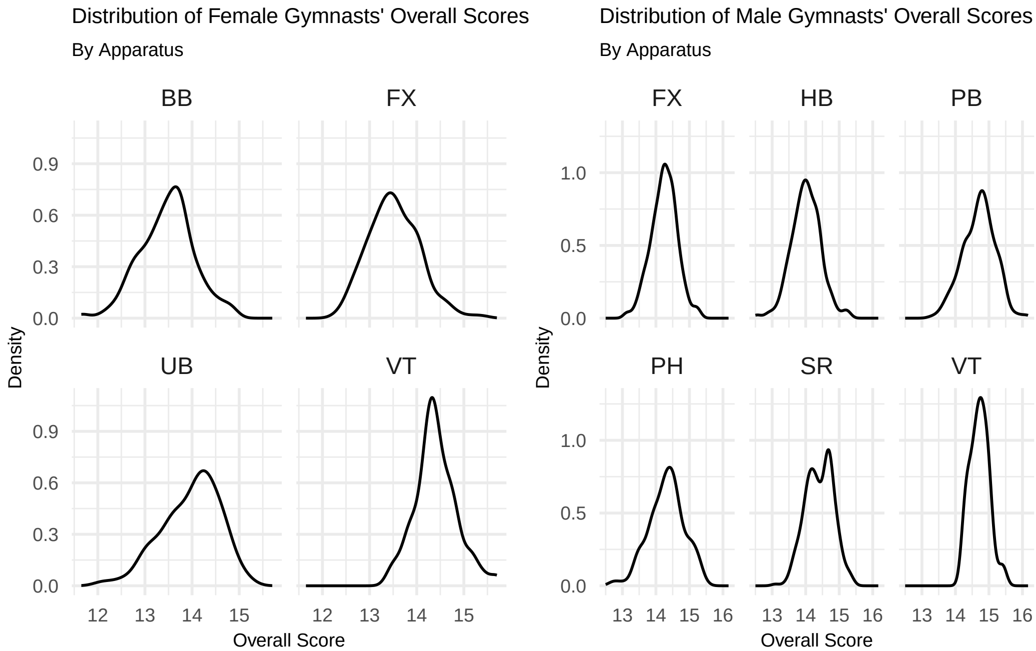
We have the following objectives for this study: (UCSAS, 2023)

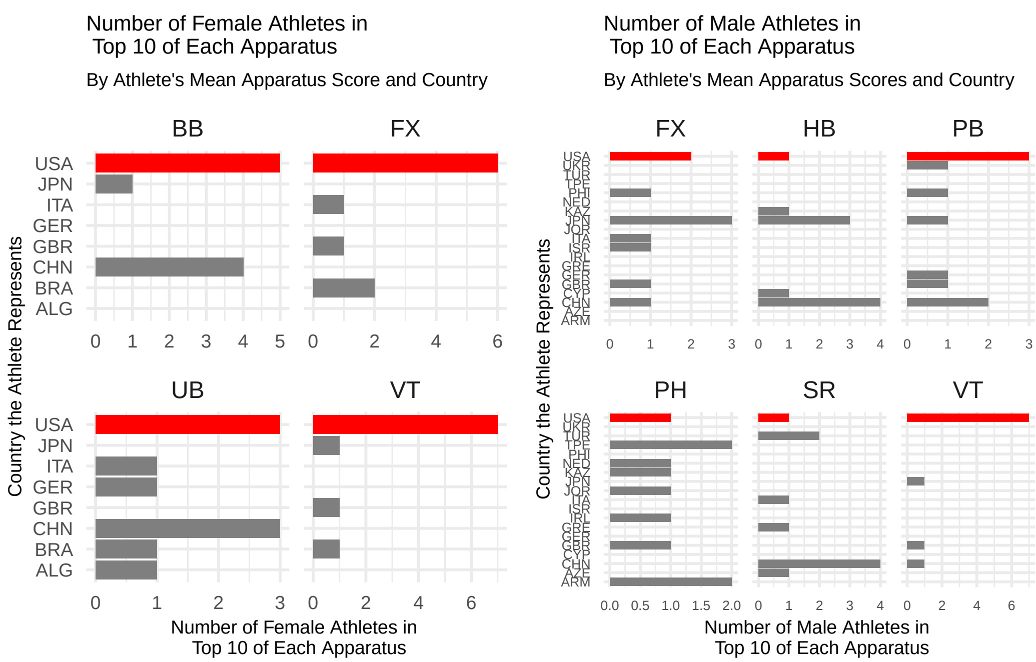
1) Decide on whether to maximize total medal count, gold medal count, or a weighted medal count (e.g., 3 for gold, 2 for silver, 1 for bronze).
2) Decide on whether to value the medals of an event over others. For example, consider a team all-around medal to be more valuable than the individual all-around medals and/or consider the individual all-around medals to be more valuable than the individual apparatus medals.
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. This should consider under what circumstances can Team USA maximize its total medal count by selecting a gymnast who only competes on 1 apparatus (e.g., Stephen Nederoscik, 2021 pommel horse World Champion).
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 using an analytical model.

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, Yang and Swartz use Monte Carlo Markov Chains to simulate the outcomes of baseball games (Yang et. al., 2022). 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 created some exploratory data visualizations to examine the distributions of athlete scores and examine the performance of US athletes relative to other countries. We find that from the density plots of male and female athletes' overall scores (difficulty score + execution score - penalty = overall score) per apparatus that the scores are approximately normally distributed for the apparatuses for both genders. There are some slight deviations from normality, namely women's vault scores and uneven bars scores are slightly skewed left and men's still rings scores have a slight dip in the peak. Nonetheless, the approximate normality of the distribution of athlete's scores by apparatus informs our bayesian approach, as we may use normal priors for our data. Furthermore, we plotted the number of athletes per country in the top 10 of each apparatus internationally, top 10 meaning the athletes with top 10 highest mean scores for each apparatus. For example, we see that for women's vault, 6 of the top 10 athletes in the world are US gymnasts. 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. In the men's case, we may not want to send specialists to take up a spot on team of five, and we shall explore this conjecture in our simulations.




## Methodology

Prior to conducting simulations, we cleaned our data set on the 2022-2023 gymnastics competition results. 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 made sure to add in missing names and account 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 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.

We then proceeded to cut down on the number of observations in our data set for two purposes: 1) so that our simulations later could run more quickly, and 2) we felt that it was unnecessary to simulate scores for athletes that had little to no chance of medaling given their previous records, given the scarcity of athletes that will attend the Olympic finals. 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. Afterwards, 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 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. Additionally, filtering for athletes' scores when an athleted has competed in that apparatus more than twice allows us to find a variance and mean for that athlete's performance on an 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.

## Simulations

### Bayesian Monte Carlo Model

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 historical performance data, conditioning these distributions on individual competition results, and simulating medal outcomes by predicting scores for each gymnast in each apparatus event. The approach offers a robust framework for incorporating 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 $i$. This allows us to write the posterior distribution as:

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

To simulate a score for an athlete we sample $\theta^{(s)} \sim p(\theta|x_i)$ from the posterior distribution and then a new value, and then sample $\tilde{x_i} \sim p(x|\theta^{(s)})$. This represents a new predicted data point for athlete $i$ using the posterior distribution, 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:

We began by creating prior distributions for each apparatus' total score. Splitting the data set by apparatus and gender resulted in multiple separate smaller data sets, see Exploratory Data Visualizations for the apparatus-gender level distribution. Observing the combined score distributions, they appear to be unimodal and slightly right-skewed. Various distributions were considered, like the beta distribution which is conveniently upper and lower-bounded, but the normal distribution was chosen for its simplicity, ease of use, and effective fit.

For ease of use, we depended on conjugacy to derive the parameters of the normal distribution. Since both the mean, $mu$, and variance, $sigma^2$, of the normal distribution are unknown, we used normal-inverse gamma priors for both parameters. At this point, the issue arises that a plurality of athletes have only ever done a single competition in any given apparatus, resulting in a large amount of athletes with 0 variance 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.

To estimate prior parameters, we fit a normal distribution to the distribution of athletes' means from the data using the maximum likelihood method and the `fitdist()` function (Muller, 2023). The maximum likelihood estimates for the mean and variance were then used as the prior parameters for the normal part of the normal-inverse gamma distribution. Similarly, for the inverse-gamma parameters, we fit an inverse-gamma distribution to the distribution of athlete's variances from the data using a similar method and used these parameters as the prior parameters for the inverse-gamma part of the normal-inverse gamma distribution. This process was done independently for all apparatus-gender combinations to produce a different set of prior parameters for each independently.

### Conditioning on Individual Results:

Following the establishment of the prior distributions, we updated these distributions based on individual 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 1000 times per athlete.

### Simulation of Gymnastics Events:

To simulate gymnastics events, we performed 500 iterations for each apparatus event. For every iteration, we simulated a score for each athlete in the event by sampling $\tilde{x_i}$ from the posterior distribution. Furthermore, since the normal distribution is unbounded, we truncated the 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 introduced more variance in the medal distribution, which we take into account when identifying which athletes to pick for Team USA. We repeated the simulation process for each apparatus event, resulting in about 11 million simulated scores across all competitions.

### Assumptions:

Inherent in our methodology are several assumptions. Firstly, we assume that gymnastic scores are normally distributed, justifying the use of the normal distribution for both prior and posterior distributions. Additionally, we assume independence between events, 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. Overall, the most successful American athletes were:

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Indicating that the most successful american team would likely be composed of:

## LIST HERE PLZ

With a total of (number of medals) across 500 simulations of each apparatus.

### Female Athletes' Results

For women's apparatuses, we outputted the tables of simulation outcomes for floor exercise, balance beam, and vault because of the high presence of medals for US gymnasts. The table of simulation outcomes for uneven bars is in the appendix.

Table 1: Women's Floor Exercise Simulation Results

| Athlete & Country | Golds | Silvers | Bronzes | Total Medals |
|---|---|---|---|---|
| Simone Biles: USA | 206 | 68 | 61 | 335 |
| Rebeca Andrade: BRA | 48 | 63 | 51 | 162 |
| Kaliya Lincoln: USA | 37 | 35 | 34 | 106 |
| Jessica Gadirova: GBR | 30 | 36 | 36 | 102 |
| Jade Carey: USA | 18 | 27 | 36 | 81 |
| Flavia Saraiva: BRA | 22 | 33 | 19 | 74 |
| Shilese Jones: USA | 12 | 22 | 28 | 62 |
| Martina Maggio: ITA | 14 | 22 | 25 | 61 |
| Jordan Chiles: USA | 20 | 20 | 21 | 61 |
| Joscelyn Roberson: USA | 15 | 11 | 18 | 44 |

Table 2: Women's Balance Beam Simulation Results

| Athlete & Country | Golds | Silvers | Bronzes | Total Medals |
|---|---|---|---|---|
| Simone Biles: USA | 93 | 61 | 54 | 208 |
| Yaqin Zhou: CHN | 73 | 71 | 44 | 188 |
| Konnor McClain: USA | 80 | 43 | 43 | 166 |
| Qingying Zhang: CHN | 55 | 58 | 37 | 150 |
| Sunisa Lee: USA | 34 | 30 | 40 | 104 |
| Yushan Ou: CHN | 21 | 24 | 27 | 72 |
| Huan Luo: CHN | 18 | 13 | 21 | 52 |
| Urara Ashikawa: JPN | 13 | 15 | 21 | 49 |
| Skye Blakely: USA | 11 | 16 | 14 | 41 |
| NA | 7 | 5 | 18 | 30 |

Table 3: Women's Vault Simulation Results

| Athlete & Country | Golds | Silvers | Bronzes | Total Medals |
|---|---|---|---|---|
| Simone Biles: USA | 176 | 100 | 58 | 334 |
| Rebeca Andrade: BRA | 108 | 99 | 73 | 280 |
| Jade Carey: USA | 74 | 74 | 61 | 209 |
| Shilese Jones: USA | 29 | 31 | 50 | 110 |
| Konnor McClain: USA | 18 | 37 | 46 | 101 |
| Ondine Achampong: GBR | 17 | 30 | 38 | 85 |
| Joscelyn Roberson: USA | 15 | 30 | 38 | 83 |
| Shokyo Miyata: JPN | 14 | 24 | 41 | 79 |
| Jordan Chiles: USA | 12 | 34 | 31 | 77 |
| Skye Blakely: USA | 22 | 16 | 36 | 74 |

### Male Athletes' Results

For men's apparatuses, we outputted the tables of simulation outcomes for vault and parallel bars because of the high presence of medals for US gymnasts relative to the other apparatuses. The tables of simulation outcomes for floor exercise, still rings, pommel horse, and high bar are in the appendix.

Table 4: Men's Vault Simulation Results

| Athlete & Country | Golds | Silvers | Bronzes | Total Medals |
|---|---|---|---|---|
| Jake Jarman: GBR | 103 | 53 | 61 | 217 |
| Asher Hong: USA | 63 | 52 | 59 | 174 |
| Daiki Hashimoto: JPN | 55 | 46 | 48 | 149 |
| Boheng Zhang: CHN | 47 | 48 | 36 | 131 |
| Donnell Whittenburg: USA | 43 | 47 | 37 | 127 |
| Khoi Young: USA | 37 | 45 | 39 | 121 |
| Curran Phillips: USA | 33 | 39 | 36 | 108 |
| Dallas Hale: USA | 28 | 44 | 31 | 103 |
| Taylor Burkhart: USA | 25 | 38 | 31 | 94 |
| Colt Walker: USA | 21 | 25 | 36 | 82 |

Table 5: Men's Parallel Bars Simulation Results

| Athlete & Country | Golds | Silvers | Bronzes | Total Medals |
|---|---|---|---|---|
| Jingyuan Zou: CHN | 192 | 75 | 46 | 313 |
| Lukas Dauser: GER | 38 | 53 | 41 | 132 |
| Boheng Zhang: CHN | 38 | 33 | 30 | 101 |
| Carlos Yulo: PHI | 23 | 27 | 23 | 73 |
| Blake Sun: USA | 20 | 21 | 23 | 64 |
| Curran Phillips: USA | 17 | 23 | 24 | 64 |
| Illia Kovtun: UKR | 14 | 21 | 28 | 63 |
| Joe Fraser: GBR | 18 | 24 | 17 | 59 |
| Colt Walker: USA | 19 | 15 | 22 | 56 |
| NA | 8 | 19 | 21 | 48 |

## 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 female USA medalists tend to represent a much higher proportion of medal successes (no matter the success 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, the USA, China, Brazil, and Great Britain make multiple appearances. The USA has athletes in the top 10 most decorated gold medalist for each apparatus as well as the top 5, but other countries do not (Appendix: Image 9). This allows us to assume that the USA has great potential in winning the team all-around since it is the only country with many of the most successful athletes in each apparatus in terms of the number of gold medals. 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. Also 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 slightly beneficial to the men's team to value the team's all-around success more than the 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 and pressure on one singular person. Weighing the individual all-around as 2 will hopefully benefit the women's team with Simone Biles as the potential representative for this event. These weights will in hope best accommodate the male and female athletes and give them the best chance at success against other countries in terms of the total number of gold medals.

### Objective 3: All-Around vs Event Specialist vs 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 a combination of all-around and event-specialist gymnasts. Since the US women's team has a strong shot at winning the individual all-around with multi-apparatus highly gold medal decorated athlete Simone Biles and team all-around with other multiple highly decorated gold medalists who specialize in their apparatus, focusing on both would be an optimal strategy (Appendix: Image 10). For the men's team, we believe it is best to select a team of five male athletes who are also a combination of both all-around gymnasts and specialists. In the simulation, since 3 of the top 10 most gold medal-decorated male gymnasts in parallel bars are from the US and 7 of the top 10 in vault are from the US, there is a good chance that a male athlete from the US may be successful in those apparatuses (Appendix: Image 11). Since the US does not seem to have very many strong gold medal specialists in the other apparatuses, the men's team should fill the remaining positions with all-around gymnasts.

**Objective 4: Identifying 5 Athletes ...**

## Appendix

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### Additional Simulation Results

Given women compete on 4 apparatuses and men compete on 4 apparatuses, we have tables of the simulation outcomes for all 10 apparatuses, and the 5 simluation outcome tables where US gymnasts do not perform as well relative to athletes from other countries are outputted below.

Table 6: Women’s Uneven Bars Simulation Results

| Athlete & Country | Golds | Silvers | Bronzes | Total Medals |
|---|---|---|---|---|
| Kayla Neymour: ALG | 92 | 63 | 46 | 201 |
| Qiyan Qiu: CHN | 72 | 69 | 43 | 184 |
| Shilese Jones: USA | 44 | 46 | 44 | 134 |
| Xiaoyuan Wei: CHN | 47 | 32 | 26 | 105 |
| Zoe Miller: USA | 37 | 26 | 38 | 101 |
| Alice D’Amato: ITA | 30 | 29 | 32 | 91 |
| Xijing Tang: CHN | 28 | 27 | 31 | 86 |
| Rebeca Andrade: BRA | 22 | 28 | 31 | 81 |
| Simone Biles: USA | 11 | 22 | 21 | 54 |
| Elisabeth Seitz: GER | 15 | 22 | 16 | 53 |

Table 7: Men's Floor Exercise Simulation Results

| Athlete & Country | Golds | Silvers | Bronzes | Total Medals |
|---|---|---|---|---|
| Carlos Yulo: PHI | 62 | 43 | 47 | 152 |
| Artem Dolgopyat: ISR | 33 | 29 | 26 | 88 |
| Ryosuke Doi: JPN | 32 | 21 | 24 | 77 |
| Paul Juda: USA | 17 | 20 | 21 | 58 |
| Daiki Hashimoto: JPN | 19 | 15 | 22 | 56 |
| Brody Malone: USA | 18 | 18 | 14 | 50 |
| NA | 13 | 20 | 16 | 49 |
| Boheng Zhang: CHN | 23 | 10 | 13 | 46 |
| Kazuki Minami: JPM | 19 | 16 | 8 | 43 |
| Nicola Bartolini: ITA | 13 | 18 | 10 | 41 |

Table 8: Men's High Bar Simulation Results

| Athlete & Country | Golds | Silvers | Bronzes | Total Medals |
|---|---|---|---|---|
| Daiki Hashimoto: JPN | 62 | 60 | 22 | 144 |
| Cong Shi: CHN | 57 | 30 | 23 | 110 |
| Boheng Zhang: CHN | 52 | 32 | 25 | 109 |
| Wei Sun: CHN | 30 | 24 | 26 | 80 |
| Brody Malone: USA | 29 | 27 | 20 | 76 |
| Milad Karimi: KAZ | 16 | 30 | 20 | 66 |
| Weide Su: CHN | 31 | 18 | 15 | 64 |
| Ilias Georgiou: CYP | 8 | 20 | 21 | 49 |
| Shohei Kawakami: JPN | 13 | 20 | 15 | 48 |
| NA | 18 | 12 | 15 | 45 |

Table 9: Men's Pommel Horse Simulation Results

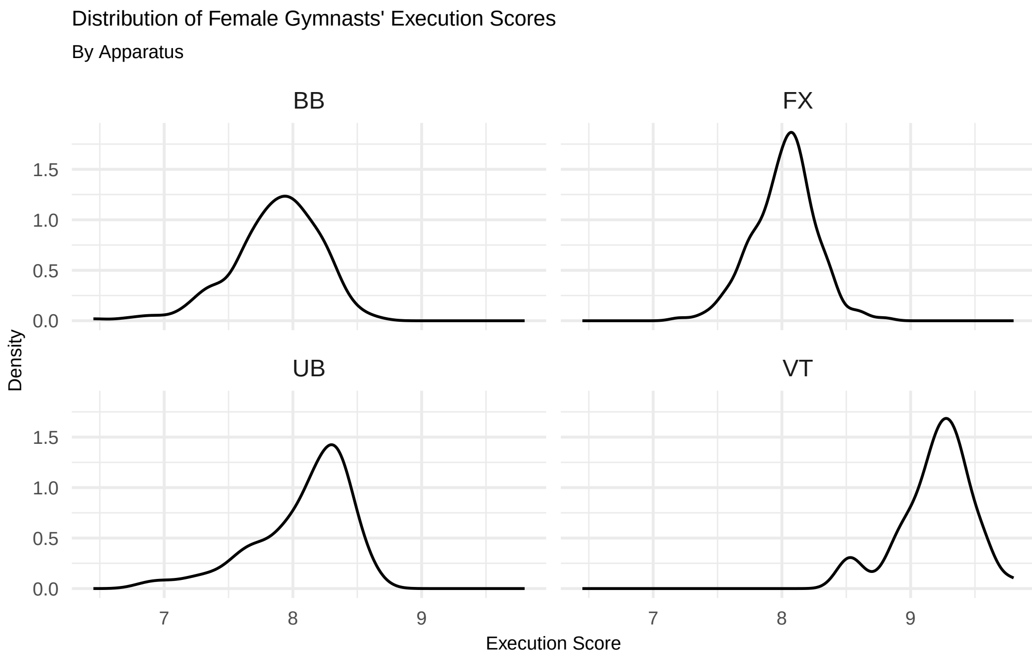
| Athlete & Country | Golds | Silvers | Bronzes | Total Medals |
|---|---|---|---|---|
| Max Whitlock: GBR | 93 | 41 | 37 | 171 |
| Nariman Kurbanov: KAZ | 62 | 47 | 35 | 144 |
| Chih Lee: TPE | 55 | 37 | 39 | 131 |
| Rhys McClenaghan: IRL | 26 | 33 | 24 | 83 |
| Ahmad Abu Al Soud: JOR | 25 | 20 | 28 | 73 |
| Gagik Khachikyan: ARM | 22 | 29 | 15 | 66 |
| Stephen Nedoroscik: USA | 20 | 19 | 26 | 65 |
| NA | 20 | 25 | 16 | 61 |
| NA | 16 | 20 | 19 | 55 |
| NA | 18 | 12 | 15 | 45 |

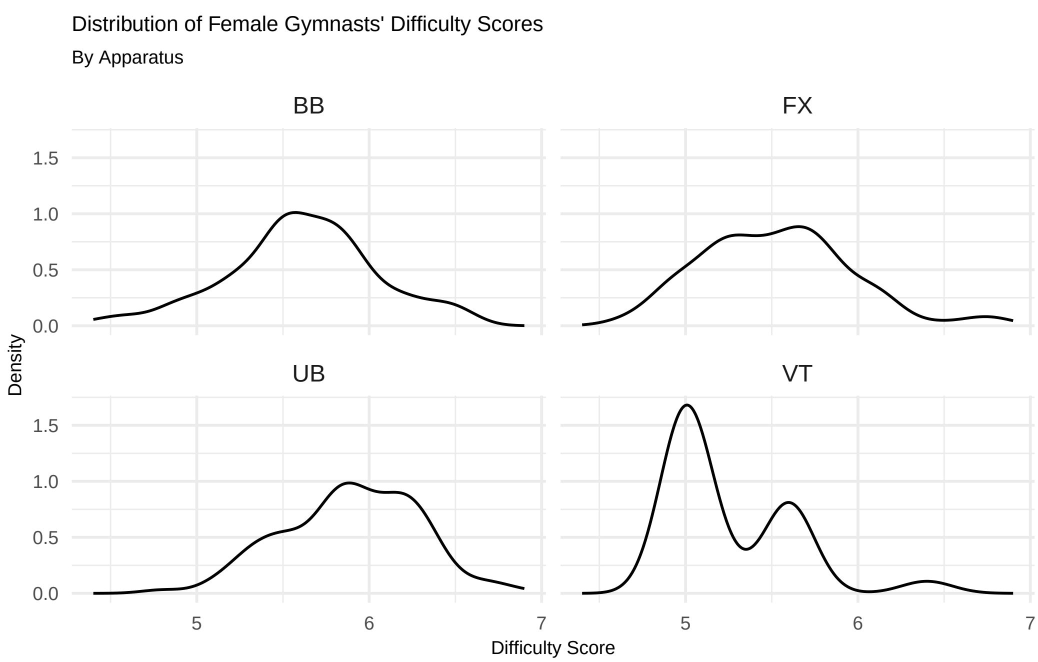
Table 10: Men's Still Rings Simulation Results

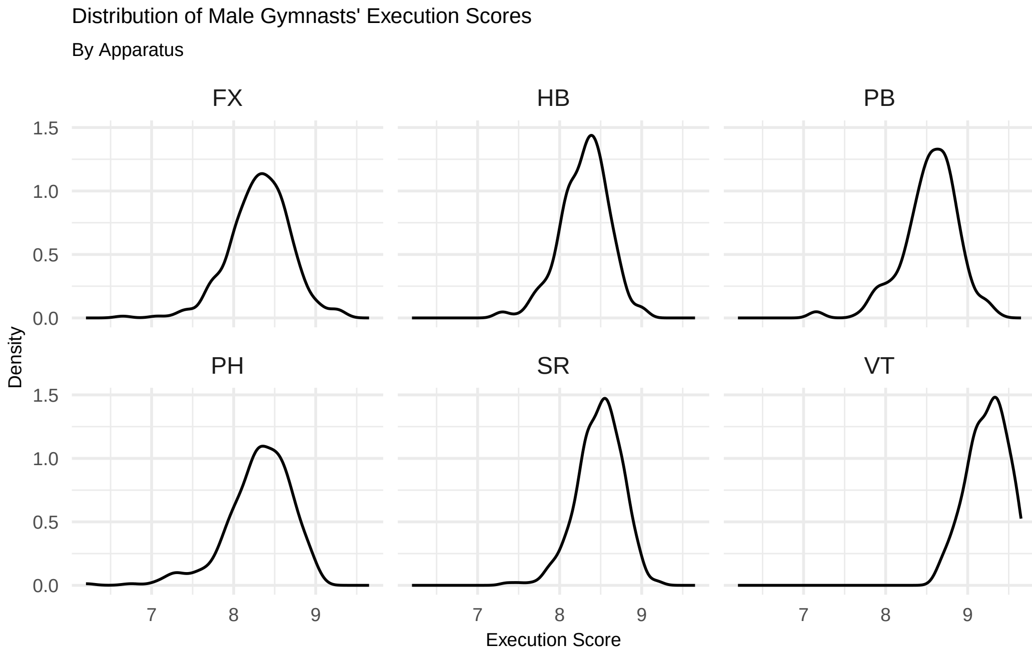
| Athlete & Country | Golds | Silvers | Bronzes | Total Medals |
|---|---|---|---|---|
| Yang Liu: CHN | 92 | 57 | 35 | 184 |
| Xingyu Lan: CHN | 68 | 34 | 48 | 150 |
| Eleftherious Petrounias: GRE | 27 | 49 | 39 | 115 |
| Jingyuan Zou: CHN | 47 | 22 | 29 | 98 |
| Adem Asil: TUR | 17 | 29 | 33 | 79 |
| Salvatore Maresca: ITA | 22 | 18 | 33 | 73 |
| Ibrahim Colak: TUR | 15 | 23 | 18 | 56 |
| Hao You: CHN | 14 | 27 | 15 | 56 |
| NA | 18 | 18 | 19 | 55 |
| Boheng Zhang: CHN | 15 | 16 | 20 | 51 |

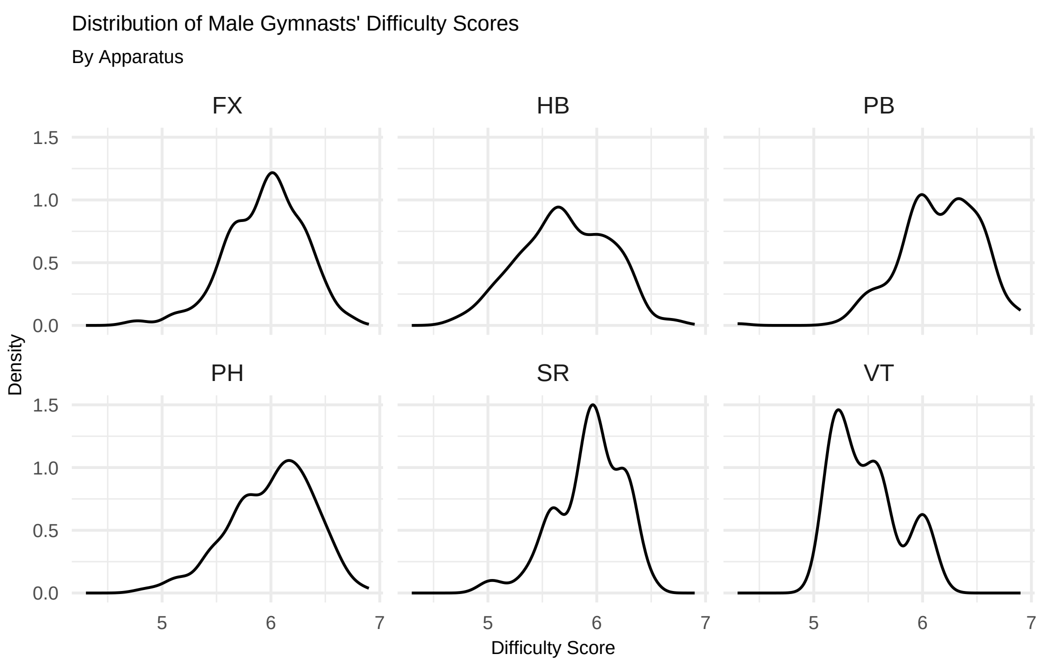
### Extra Visualizations

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.

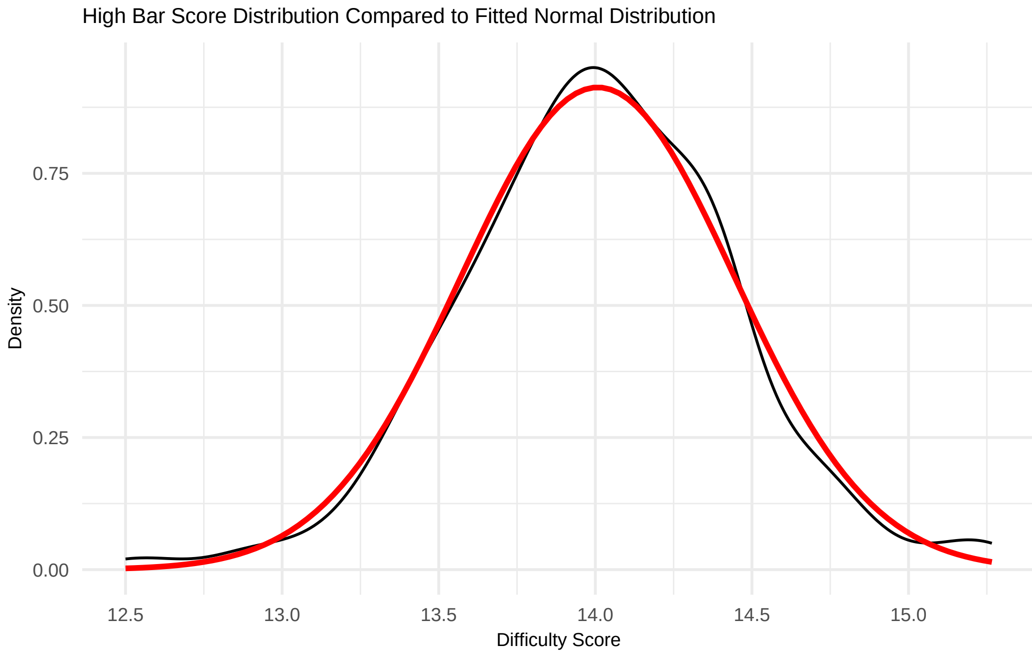


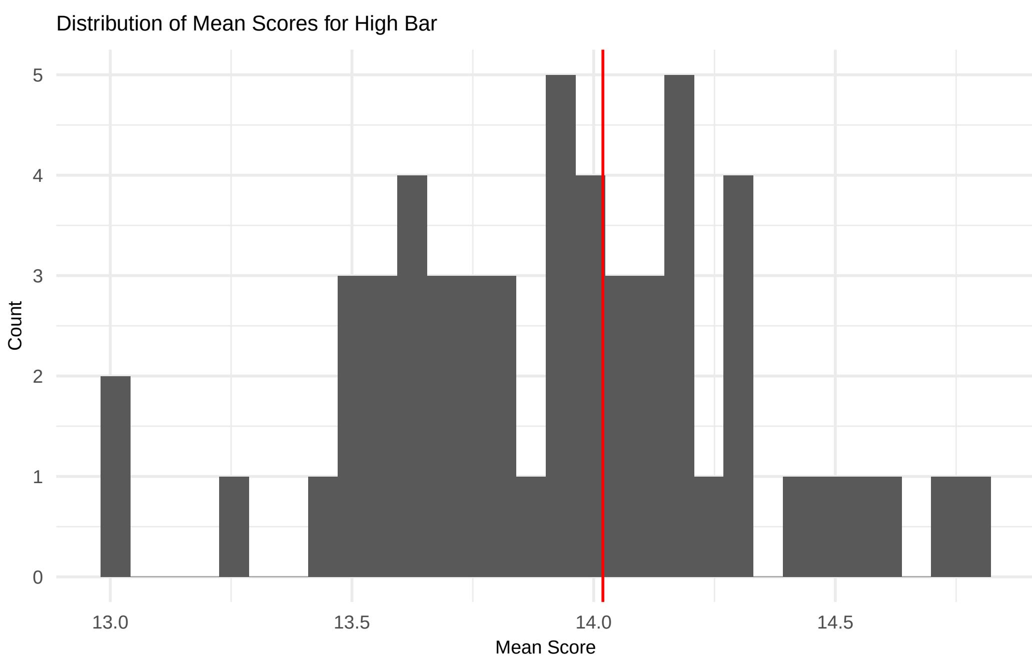



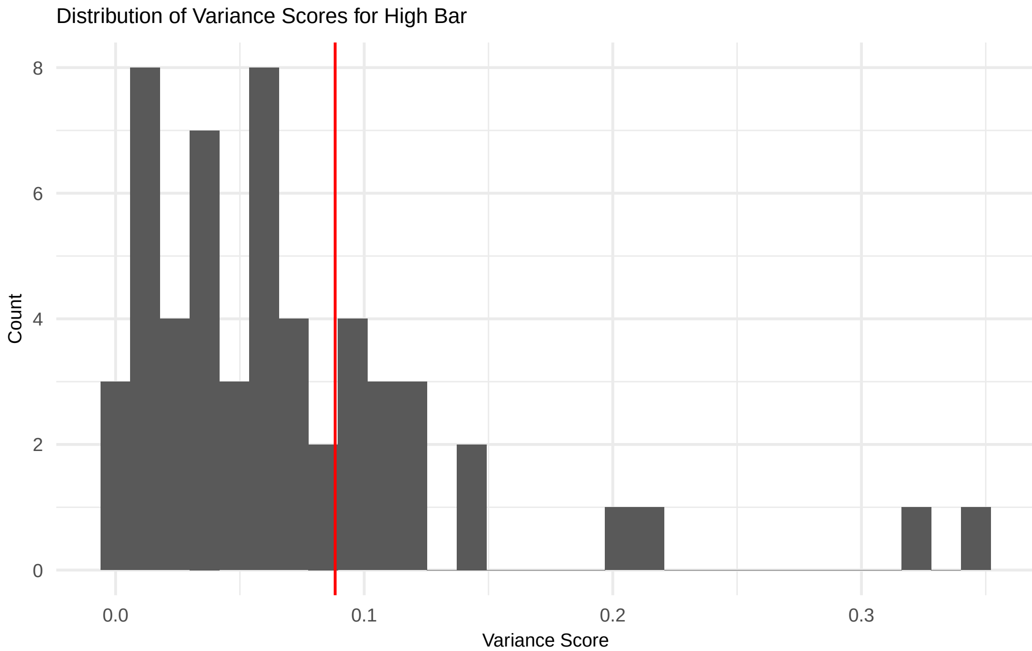


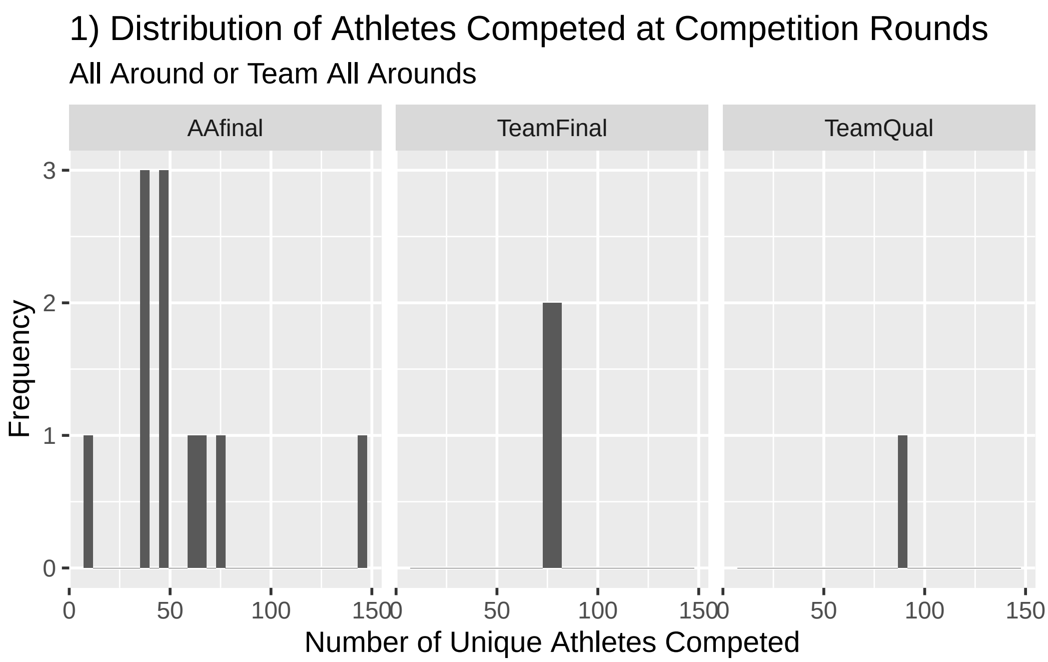




Additionally, we look at the distribution of mean scores and the distribution of variance scores for men's high bar apparatus as an example of how we will fit normal-inverse gamma priors for the means and variances. We can see that the distribution of mean scores follows an approximately normal distribution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

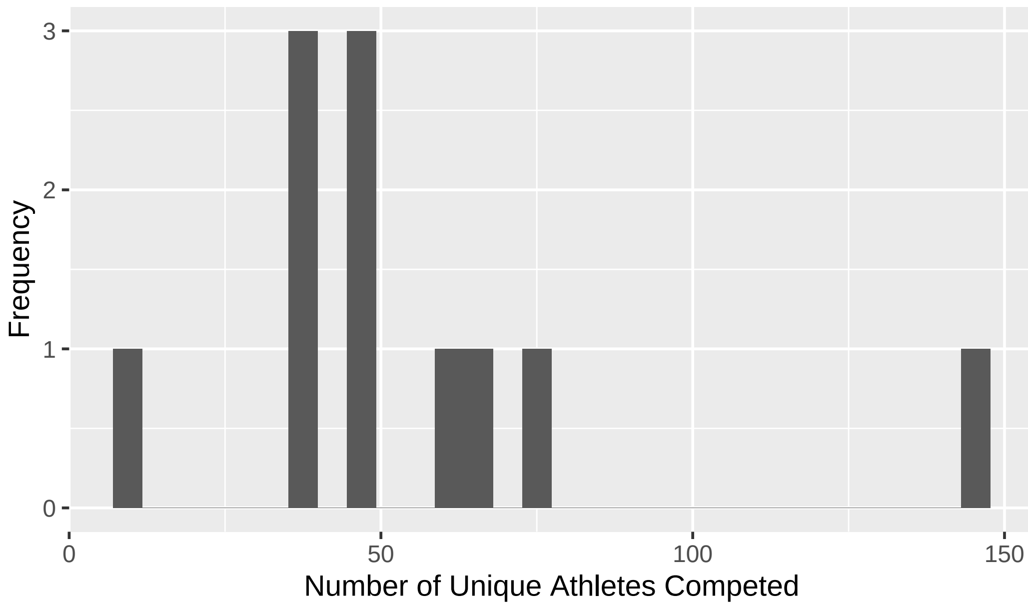

High Bar Score Distribution Compared to Fitted Normal Distribution
Density
0.75
0.50
0.25
0.00
12.5
13.0
13.5
14.0
14.5
15.0
Difficulty Score


Distribution of Mean Scores for High Bar
Count
5
4
3
2
1
0
13.0
13.5
14.0
14.5
Mean Score


Distribution of Variance Scores for High Bar
Count
0
2
4
6
8
0.0
0.1
0.2
0.3
Variance Score

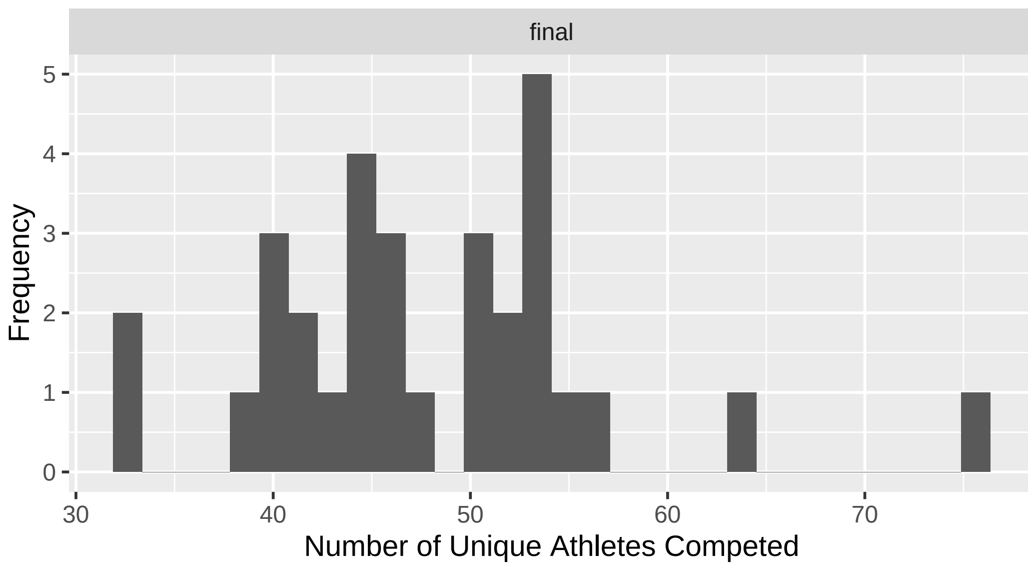

1) Distribution of Athletes Competed at Competition Rounds
All Around or Team All Arounds
AAfinal
TeamFinal
TeamQual
Frequency
0
1
2
3
0
50
100
150
Number of Unique Athletes Competed

2) Distribution of Athletes Competed at AA Finals




3) Distribution of Athletes Competed at Final Rounds

Individual Apparatuses



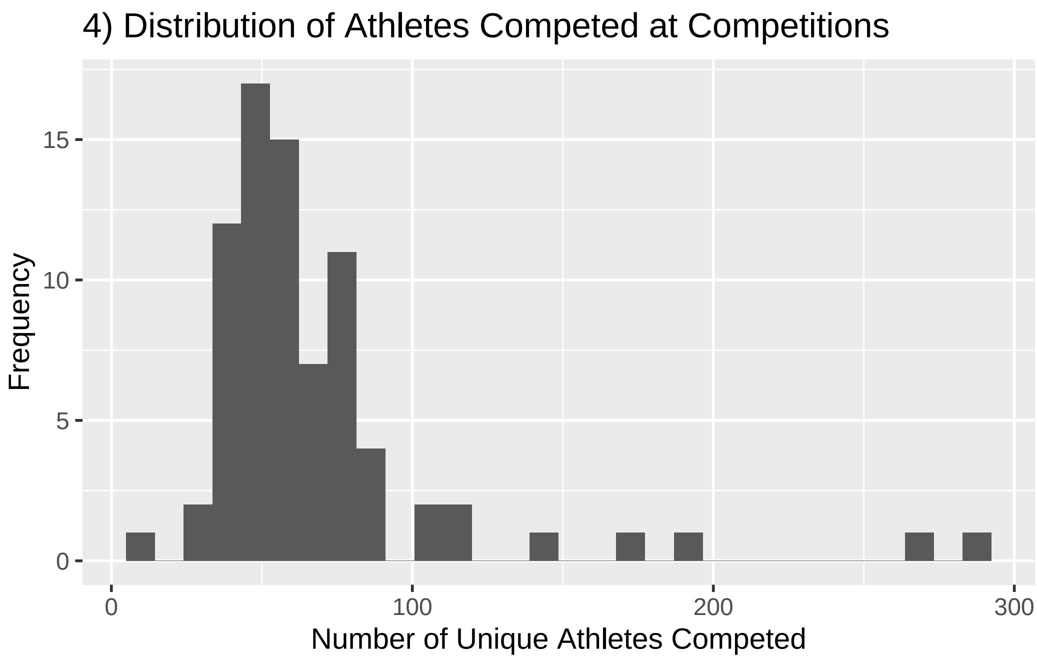
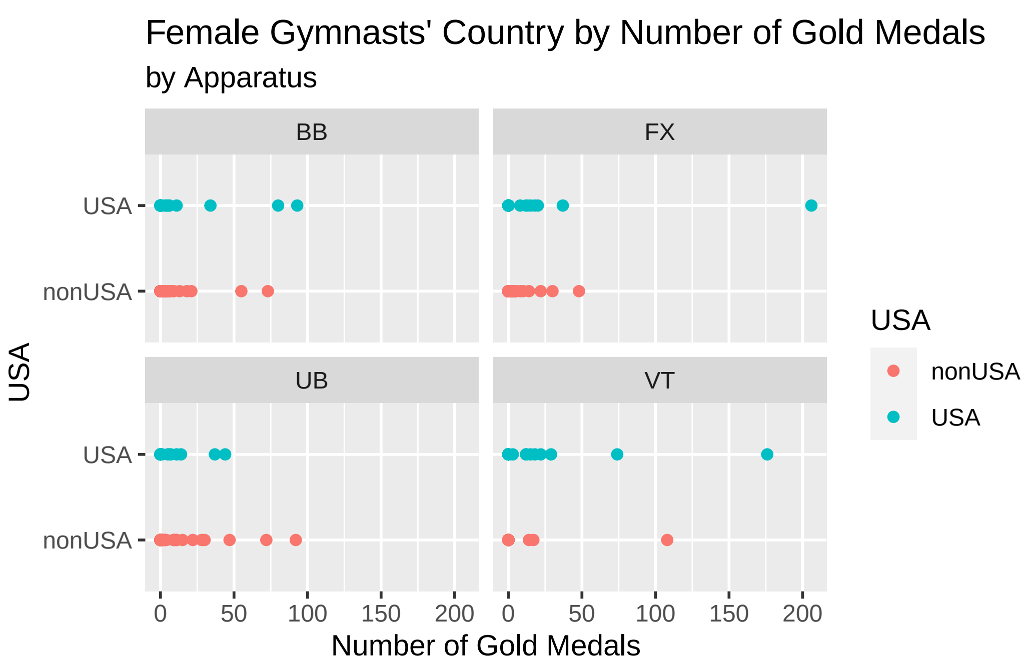
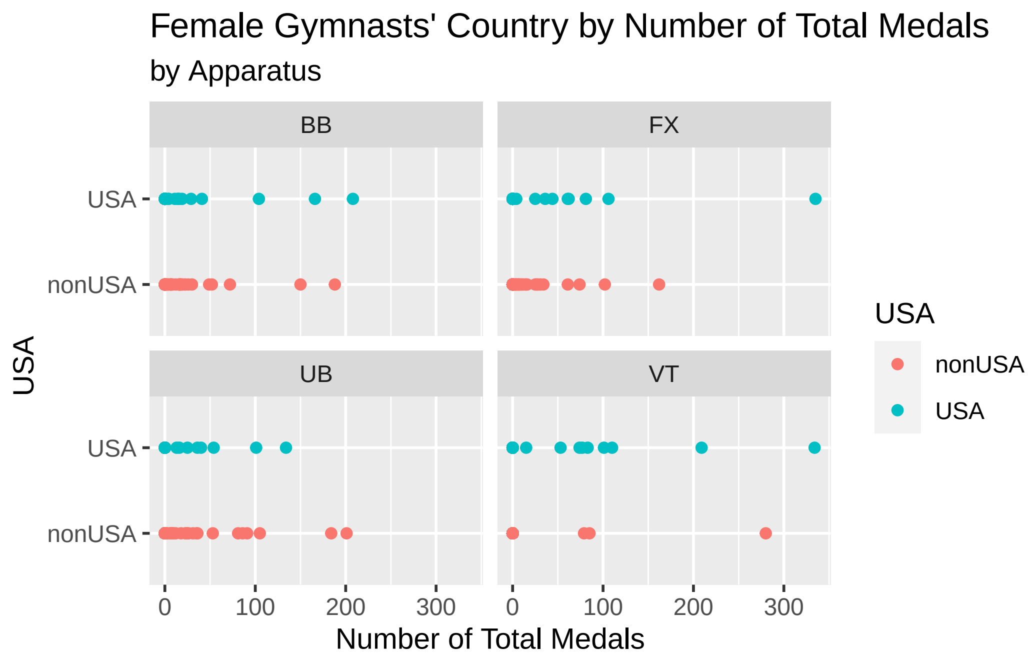

4) Distribution of Athletes Competed at Competitions
Frequency
15
10
5
0
0
100
200
300
Number of Unique Athletes Competed

**Image 5)**


Female Gymnasts' Country by Number of Gold Medals
by Apparatus
BB
FX
UB
VT
USA
nonUSA
USA
0
50
100
150
200
Number of Gold Medals
USA
nonUSA
USA


Female Gymnasts' Country by Number of Total Medals
by Apparatus
BB
FX
UB
VT
USA
nonUSA
0
100
200
300
Number of Total Medals
USA
nonUSA
USA

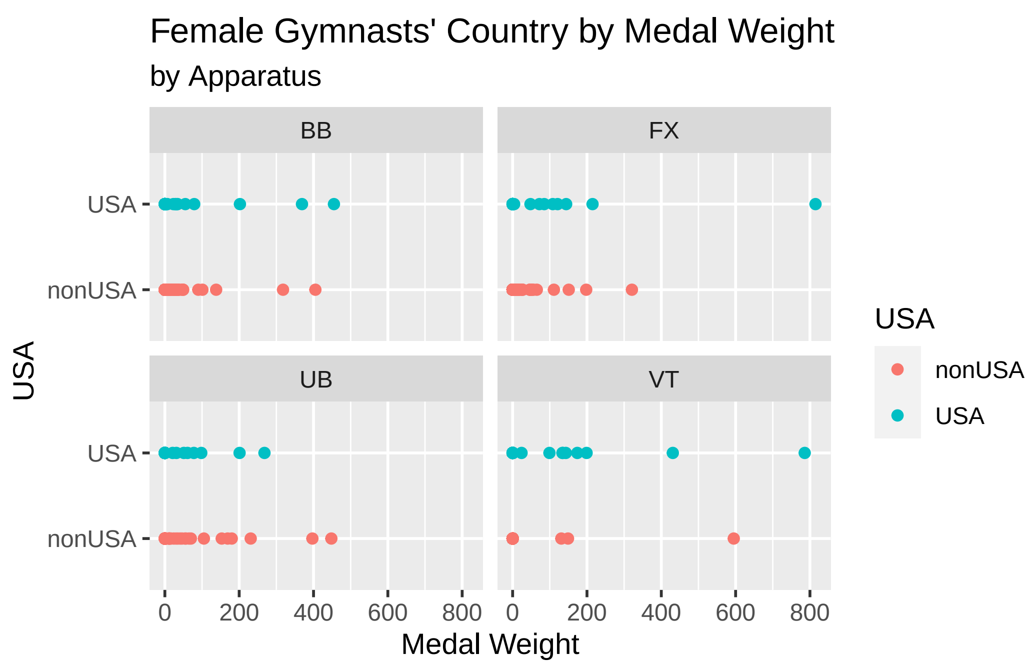
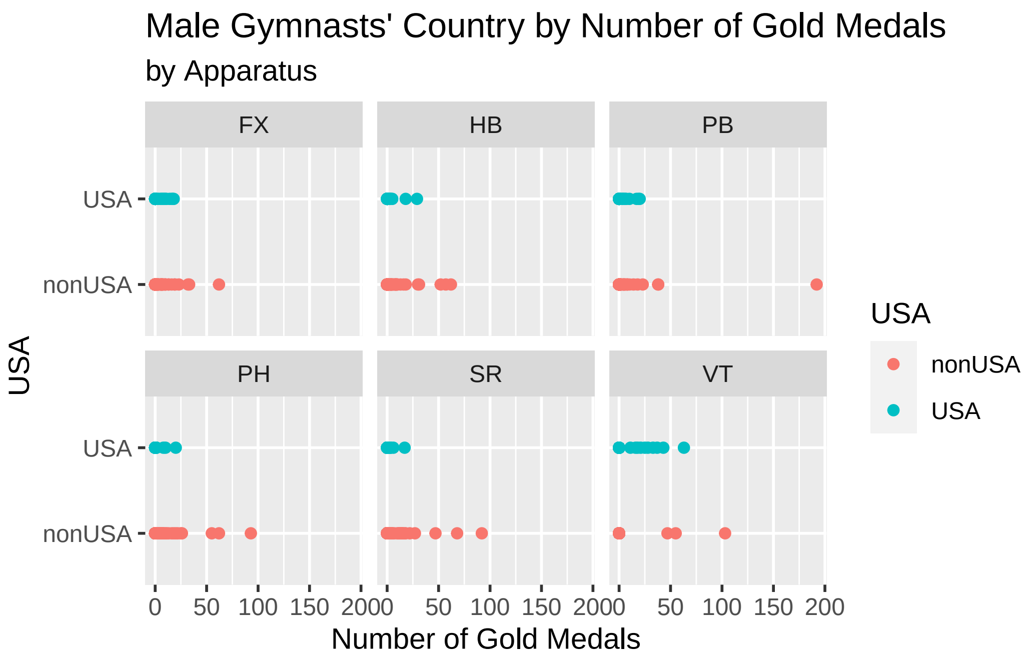
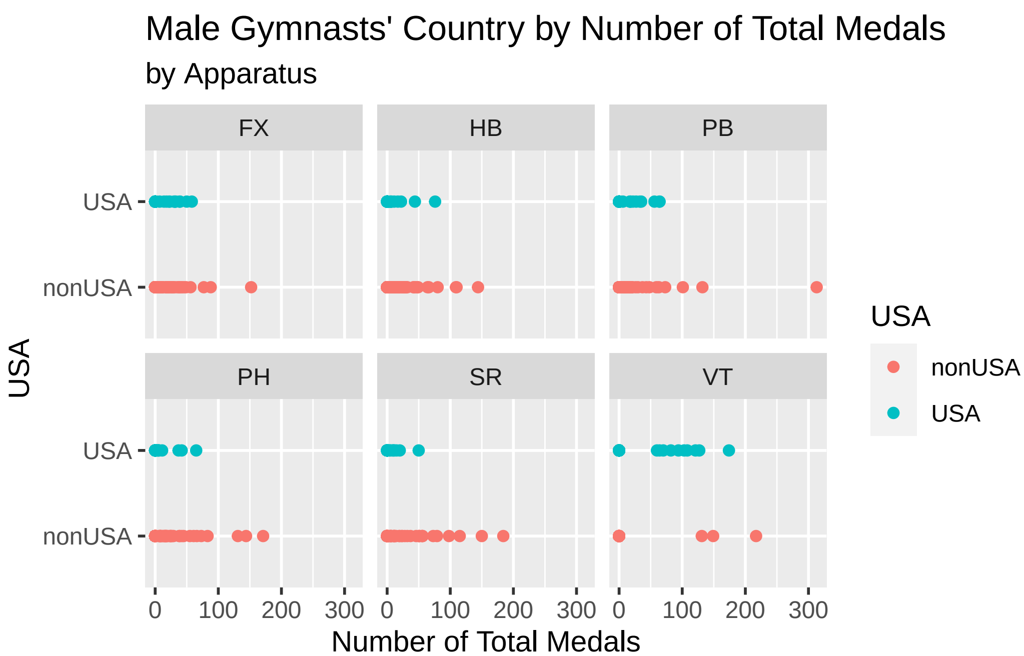

Female Gymnasts' Country by Medal Weight
by Apparatus
BB
FX
UB
VT
USA
nonUSA
0
200
400
600
800
Medal Weight
USA
nonUSA
USA

**Image 6)**



Male Gymnasts' Country by Number of Gold Medals
by Apparatus
FX
HB
PB
PH
SR
VT
USA
nonUSA
0 50 100 150 200
Number of Gold Medals
USA
nonUSA
USA

Male Gymnasts' Country by Number of Total Medals
by Apparatus
FX
HB
PB
PH
SR
VT
USA
nonUSA
0 100 200 300
Number of Total Medals
USA
nonUSA
USA

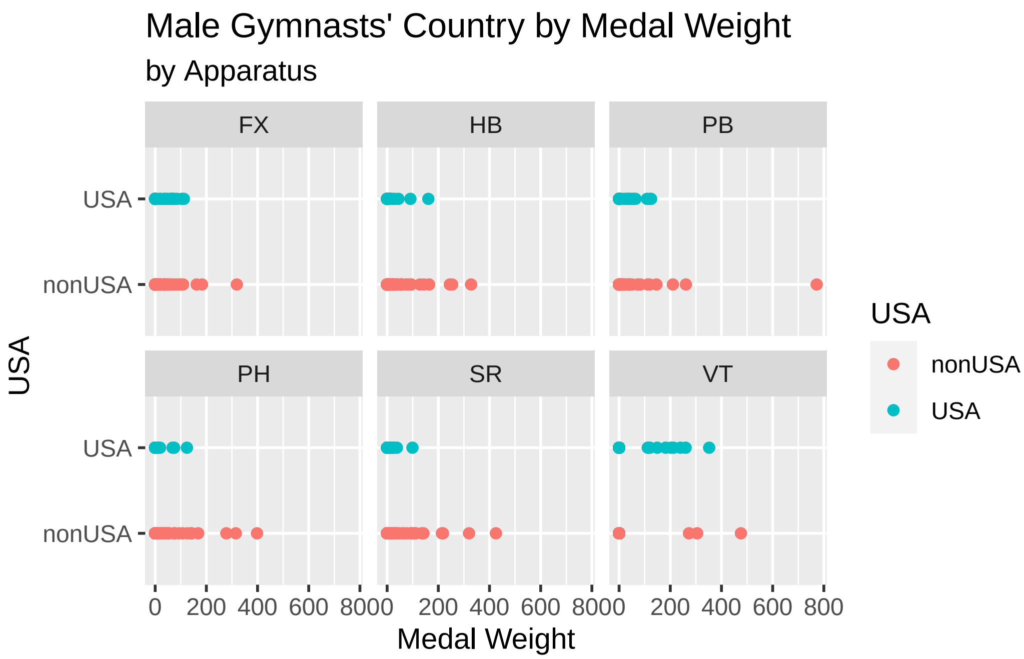



**Image 7)**

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

| unique_id | Golds | Silvers | Bronzes | Total_Medals | Country | Medal_Weight | Apparatus | USA |
|---|---|---|---|---|---|---|---|---|
| SimBIL_USA | 93 | 61 | 54 | 208 | USA | 455 | BB | USA |
| KonMCC_USA | 80 | 43 | 43 | 166 | USA | 369 | BB | USA |
| YaqZHO_CHN | 73 | 71 | 44 | 188 | CHN | 405 | BB | nonUSA |
| QinZHA_CHN | 55 | 58 | 37 | 150 | CHN | 318 | BB | nonUSA |
| SunLEE_USA | 34 | 30 | 40 | 104 | USA | 202 | BB | USA |
| SimBIL_USA | 206 | 68 | 61 | 335 | USA | 815 | FX | USA |
| RebAND_BRA | 48 | 63 | 51 | 162 | BRA | 321 | FX | nonUSA |
| KalLIN_USA | 37 | 35 | 34 | 106 | USA | 215 | FX | USA |
| JesGAD_GBR | 30 | 36 | 36 | 102 | GBR | 198 | FX | nonUSA |
| FlaSAR_BRA | 22 | 33 | 19 | 74 | BRA | 151 | FX | nonUSA |
| KayNEM_ALG | 92 | 63 | 46 | 201 | ALG | 448 | UB | nonUSA |
| QiyQIU_CHN | 72 | 69 | 43 | 184 | CHN | 397 | UB | nonUSA |
| XiaWEI_CHN | 47 | 32 | 26 | 105 | CHN | 231 | UB | nonUSA |
| ShiJON_USA | 44 | 46 | 44 | 134 | USA | 268 | UB | USA |
| ZoeMIL_USA | 37 | 26 | 38 | 101 | USA | 201 | UB | USA |
| SimBIL_USA | 176 | 100 | 58 | 334 | USA | 786 | VT | USA |
| RebAND_BRA | 108 | 99 | 73 | 280 | BRA | 595 | VT | nonUSA |
| JadCAR_USA | 74 | 74 | 61 | 209 | USA | 431 | VT | USA |
| ShiJON_USA | 29 | 31 | 50 | 110 | USA | 199 | VT | USA |
| SkyBLA_USA | 22 | 16 | 36 | 74 | USA | 134 | VT | USA |

| unique_id | Golds | Silvers | Bronzes | Total_Medals | Country | Medal_Weight | Apparatus | USA |
|---|---|---|---|---|---|---|---|---|
| SimBIL_USA | 93 | 61 | 54 | 208 | USA | 455 | BB | USA |
| YaqZHO_CHN | 73 | 71 | 44 | 188 | CHN | 405 | BB | nonUSA |
| KonMCC_USA | 80 | 43 | 43 | 166 | USA | 369 | BB | USA |
| QinZHA_CHN | 55 | 58 | 37 | 150 | CHN | 318 | BB | nonUSA |
| SunLEE_USA | 34 | 30 | 40 | 104 | USA | 202 | BB | USA |
| SimBIL_USA | 206 | 68 | 61 | 335 | USA | 815 | FX | USA |
| RebAND_BRA | 48 | 63 | 51 | 162 | BRA | 321 | FX | nonUSA |
| KalLIN_USA | 37 | 35 | 34 | 106 | USA | 215 | FX | USA |
| JesGAD_GBR | 30 | 36 | 36 | 102 | GBR | 198 | FX | nonUSA |
| JadCAR_USA | 18 | 27 | 36 | 81 | USA | 144 | FX | USA |
| KayNEM_ALG | 92 | 63 | 46 | 201 | ALG | 448 | UB | nonUSA |
| QiyQIU_CHN | 72 | 69 | 43 | 184 | CHN | 397 | UB | nonUSA |
| ShiJON_USA | 44 | 46 | 44 | 134 | USA | 268 | UB | USA |
| XiaWEI_CHN | 47 | 32 | 26 | 105 | CHN | 231 | UB | nonUSA |
| ZoeMIL_USA | 37 | 26 | 38 | 101 | USA | 201 | UB | USA |
| SimBIL_USA | 176 | 100 | 58 | 334 | USA | 786 | VT | USA |
| RebAND_BRA | 108 | 99 | 73 | 280 | BRA | 595 | VT | nonUSA |
| JadCAR_USA | 74 | 74 | 61 | 209 | USA | 431 | VT | USA |
| ShiJON_USA | 29 | 31 | 50 | 110 | USA | 199 | VT | USA |
| KonMCC_USA | 18 | 37 | 46 | 101 | USA | 174 | VT | USA |

| unique_id | Golds | Silvers | Bronzes | Total_Medals | Country | Medal_Weight | Apparatus | USA |
|---|---|---|---|---|---|---|---|---|
| SimBIL_USA | 93 | 61 | 54 | 208 | USA | 455 | BB | USA |
| YaqZHO_CHN | 73 | 71 | 44 | 188 | CHN | 405 | BB | nonUSA |
| KonMCC_USA | 80 | 43 | 43 | 166 | USA | 369 | BB | USA |
| QinZHA_CHN | 55 | 58 | 37 | 150 | CHN | 318 | BB | nonUSA |
| SunLEE_USA | 34 | 30 | 40 | 104 | USA | 202 | BB | USA |
| SimBIL_USA | 206 | 68 | 61 | 335 | USA | 815 | FX | USA |
| RebAND_BRA | 48 | 63 | 51 | 162 | BRA | 321 | FX | nonUSA |
| KalLIN_USA | 37 | 35 | 34 | 106 | USA | 215 | FX | USA |
| JesGAD_GBR | 30 | 36 | 36 | 102 | GBR | 198 | FX | nonUSA |
| FlaSAR_BRA | 22 | 33 | 19 | 74 | BRA | 151 | FX | nonUSA |
| KayNEM_ALG | 92 | 63 | 46 | 201 | ALG | 448 | UB | nonUSA |
| QiyQIU_CHN | 72 | 69 | 43 | 184 | CHN | 397 | UB | nonUSA |
| ShiJON_USA | 44 | 46 | 44 | 134 | USA | 268 | UB | USA |
| XiaWEI_CHN | 47 | 32 | 26 | 105 | CHN | 231 | UB | nonUSA |
| ZoeMIL_USA | 37 | 26 | 38 | 101 | USA | 201 | UB | USA |
| SimBIL_USA | 176 | 100 | 58 | 334 | USA | 786 | VT | USA |
| RebAND_BRA | 108 | 99 | 73 | 280 | BRA | 595 | VT | nonUSA |
| JadCAR_USA | 74 | 74 | 61 | 209 | USA | 431 | VT | USA |
| ShiJON_USA | 29 | 31 | 50 | 110 | USA | 199 | VT | USA |
| KonMCC_USA | 18 | 37 | 46 | 101 | USA | 174 | VT | USA |

| USA | sumGolds | sumTotal | sumWeighted |
|---|---|---|---|
| nonUSA | 938 | 3140 | 6135 |
| USA | 1062 | 2860 | 5865 |

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

| unique_id | Golds | Silvers | Bronzes | Total_Medals | Country | Medal_Weight | Apparatus | USA |
|---|---|---|---|---|---|---|---|---|
| CarYUL_PHI | 62 | 43 | 47 | 152 | PHI | 319 | FX | nonUSA |
| ArtDOL_ISR | 33 | 29 | 26 | 88 | ISR | 183 | FX | nonUSA |
| RyoDOI_JPN | 32 | 21 | 24 | 77 | JPN | 162 | FX | nonUSA |
| BohZHA_CHN | 23 | 10 | 13 | 46 | CHN | 102 | FX | nonUSA |
| DaiHAS_JPN | 19 | 15 | 22 | 56 | JPN | 109 | FX | nonUSA |
| KazMIN_JPN | 19 | 16 | 8 | 43 | JPN | 97 | FX | nonUSA |
| DaiHAS_JPN | 62 | 60 | 22 | 144 | JPN | 328 | HB | nonUSA |
| ConSHI_CHN | 57 | 30 | 23 | 110 | CHN | 254 | HB | nonUSA |
| BohZHA_CHN | 52 | 32 | 25 | 109 | CHN | 245 | HB | nonUSA |
| WeiSU___CHN | 31 | 18 | 15 | 64 | CHN | 144 | HB | nonUSA |
| WeiSUN_CHN | 30 | 24 | 26 | 80 | CHN | 164 | HB | nonUSA |
| JinZOU_CHN | 192 | 75 | 46 | 313 | CHN | 772 | PB | nonUSA |
| LukDAU_GER | 38 | 53 | 41 | 132 | GER | 261 | PB | nonUSA |
| BohZHA_CHN | 38 | 33 | 30 | 101 | CHN | 210 | PB | nonUSA |
| CarYUL_PHI | 23 | 27 | 23 | 73 | PHI | 146 | PB | nonUSA |
| BlaSUN_USA | 20 | 21 | 23 | 64 | USA | 125 | PB | USA |
| MaxWHI_GBR | 93 | 41 | 37 | 171 | GBR | 398 | PH | nonUSA |
| NarKUR_KAZ | 62 | 47 | 35 | 144 | KAZ | 315 | PH | nonUSA |
| ChiLEE_TPE | 55 | 37 | 39 | 131 | TPE | 278 | PH | nonUSA |
| RhyMCC_IRL | 26 | 33 | 24 | 83 | IRL | 168 | PH | nonUSA |
| AhmABU_JOR | 25 | 20 | 28 | 73 | JOR | 143 | PH | nonUSA |
| YanLIU_CHN | 92 | 57 | 35 | 184 | CHN | 425 | SR | nonUSA |
| XinLAN_CHN | 68 | 34 | 48 | 150 | CHN | 320 | SR | nonUSA |
| JinZOU_CHN | 47 | 22 | 29 | 98 | CHN | 214 | SR | nonUSA |
| ElePET_GRE | 27 | 49 | 39 | 115 | GRE | 218 | SR | nonUSA |
| SalMAR_ITA | 22 | 18 | 33 | 73 | ITA | 135 | SR | nonUSA |
| JakJAR_GBR | 103 | 53 | 61 | 217 | GBR | 476 | VT | nonUSA |
| AshHON_USA | 63 | 52 | 59 | 174 | USA | 352 | VT | USA |
| DaiHAS_JPN | 55 | 46 | 48 | 149 | JPN | 305 | VT | nonUSA |
| BohZHA_CHN | 47 | 48 | 36 | 131 | CHN | 273 | VT | nonUSA |
| DonWHI_USA | 43 | 47 | 37 | 127 | USA | 260 | VT | USA |

| unique_id | Golds | Silvers | Bronzes | Total_Medals | Country | Medal_Weight | Apparatus | USA |
|---|---|---|---|---|---|---|---|---|
| CarYUL_PHI | 62 | 43 | 47 | 152 | PHI | 319 | FX | nonUSA |
| ArtDOL_ISR | 33 | 29 | 26 | 88 | ISR | 183 | FX | nonUSA |
| RyoDOI_JPN | 32 | 21 | 24 | 77 | JPN | 162 | FX | nonUSA |
| PauJUD_USA | 17 | 20 | 21 | 58 | USA | 112 | FX | USA |
| DaiHAS_JPN | 19 | 15 | 22 | 56 | JPN | 109 | FX | nonUSA |
| DaiHAS_JPN | 62 | 60 | 22 | 144 | JPN | 328 | HB | nonUSA |
| ConSHI_CHN | 57 | 30 | 23 | 110 | CHN | 254 | HB | nonUSA |
| BohZHA_CHN | 52 | 32 | 25 | 109 | CHN | 245 | HB | nonUSA |
| WeiSUN_CHN | 30 | 24 | 26 | 80 | CHN | 164 | HB | nonUSA |
| BroMAL_USA | 29 | 27 | 20 | 76 | USA | 161 | HB | USA |
| JinZOU_CHN | 192 | 75 | 46 | 313 | CHN | 772 | PB | nonUSA |
| LukDAU_GER | 38 | 53 | 41 | 132 | GER | 261 | PB | nonUSA |
| BohZHA_CHN | 38 | 33 | 30 | 101 | CHN | 210 | PB | nonUSA |
| CarYUL_PHI | 23 | 27 | 23 | 73 | PHI | 146 | PB | nonUSA |
| BlaSUN_USA | 20 | 21 | 23 | 64 | USA | 125 | PB | USA |
| CurPHI_USA | 17 | 23 | 24 | 64 | USA | 121 | PB | USA |
| MaxWHI_GBR | 93 | 41 | 37 | 171 | GBR | 398 | PH | nonUSA |
| NarKUR_KAZ | 62 | 47 | 35 | 144 | KAZ | 315 | PH | nonUSA |
| ChiLEE_TPE | 55 | 37 | 39 | 131 | TPE | 278 | PH | nonUSA |
| RhyMCC_IRL | 26 | 33 | 24 | 83 | IRL | 168 | PH | nonUSA |
| AhmABU_JOR | 25 | 20 | 28 | 73 | JOR | 143 | PH | nonUSA |
| YanLIU_CHN | 92 | 57 | 35 | 184 | CHN | 425 | SR | nonUSA |
| XinLAN_CHN | 68 | 34 | 48 | 150 | CHN | 320 | SR | nonUSA |
| ElePET_GRE | 27 | 49 | 39 | 115 | GRE | 218 | SR | nonUSA |
| JinZOU_CHN | 47 | 22 | 29 | 98 | CHN | 214 | SR | nonUSA |
| AdeASI_TUR | 17 | 29 | 33 | 79 | TUR | 142 | SR | nonUSA |
| JakJAR_GBR | 103 | 53 | 61 | 217 | GBR | 476 | VT | nonUSA |
| AshHON_USA | 63 | 52 | 59 | 174 | USA | 352 | VT | USA |
| DaiHAS_JPN | 55 | 46 | 48 | 149 | JPN | 305 | VT | nonUSA |
| BohZHA_CHN | 47 | 48 | 36 | 131 | CHN | 273 | VT | nonUSA |
| DonWHI_USA | 43 | 47 | 37 | 127 | USA | 260 | VT | USA |

| unique_id | Golds | Silvers | Bronzes | Total_Medals | Country | Medal_Weight | Apparatus | USA |
|---|---|---|---|---|---|---|---|---|
| CarYUL_PHI | 62 | 43 | 47 | 152 | PHI | 319 | FX | nonUSA |
| ArtDOL_ISR | 33 | 29 | 26 | 88 | ISR | 183 | FX | nonUSA |
| RyoDOI_JPN | 32 | 21 | 24 | 77 | JPN | 162 | FX | nonUSA |
| PauJUD_USA | 17 | 20 | 21 | 58 | USA | 112 | FX | USA |
| DaiHAS_JPN | 19 | 15 | 22 | 56 | JPN | 109 | FX | nonUSA |
| DaiHAS_JPN | 62 | 60 | 22 | 144 | JPN | 328 | HB | nonUSA |
| ConSHI_CHN | 57 | 30 | 23 | 110 | CHN | 254 | HB | nonUSA |
| BohZHA_CHN | 52 | 32 | 25 | 109 | CHN | 245 | HB | nonUSA |
| WeiSUN_CHN | 30 | 24 | 26 | 80 | CHN | 164 | HB | nonUSA |
| BroMAL_USA | 29 | 27 | 20 | 76 | USA | 161 | HB | USA |
| JinZOU_CHN | 192 | 75 | 46 | 313 | CHN | 772 | PB | nonUSA |
| LukDAU_GER | 38 | 53 | 41 | 132 | GER | 261 | PB | nonUSA |
| BohZHA_CHN | 38 | 33 | 30 | 101 | CHN | 210 | PB | nonUSA |
| CarYUL_PHI | 23 | 27 | 23 | 73 | PHI | 146 | PB | nonUSA |
| BlaSUN_USA | 20 | 21 | 23 | 64 | USA | 125 | PB | USA |
| MaxWHI_GBR | 93 | 41 | 37 | 171 | GBR | 398 | PH | nonUSA |
| NarKUR_KAZ | 62 | 47 | 35 | 144 | KAZ | 315 | PH | nonUSA |
| ChiLEE_TPE | 55 | 37 | 39 | 131 | TPE | 278 | PH | nonUSA |
| RhyMCC_IRL | 26 | 33 | 24 | 83 | IRL | 168 | PH | nonUSA |
| AhmABU_JOR | 25 | 20 | 28 | 73 | JOR | 143 | PH | nonUSA |
| YanLIU_CHN | 92 | 57 | 35 | 184 | CHN | 425 | SR | nonUSA |
| XinLAN_CHN | 68 | 34 | 48 | 150 | CHN | 320 | SR | nonUSA |
| ElePET_GRE | 27 | 49 | 39 | 115 | GRE | 218 | SR | nonUSA |
| JinZOU_CHN | 47 | 22 | 29 | 98 | CHN | 214 | SR | nonUSA |
| AdeASI_TUR | 17 | 29 | 33 | 79 | TUR | 142 | SR | nonUSA |
| JakJAR_GBR | 103 | 53 | 61 | 217 | GBR | 476 | VT | nonUSA |
| AshHON_USA | 63 | 52 | 59 | 174 | USA | 352 | VT | USA |
| DaiHAS_JPN | 55 | 46 | 48 | 149 | JPN | 305 | VT | nonUSA |
| BohZHA_CHN | 47 | 48 | 36 | 131 | CHN | 273 | VT | nonUSA |
| DonWHI_USA | 43 | 47 | 37 | 127 | USA | 260 | VT | USA |

| USA | sumGolds | sumTot | sumWeighted |
|---|---|---|---|
| nonUSA | 2333 | 6716 | 13589 |
| USA | 667 | 2284 | 4411 |

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)**

```
# A tibble: 41 x 5
# Groups:   Apparatus [4]
   unique_id  Golds Country Apparatus USA
   <chr>      <dbl> <fct>   <chr>     <fct>
 1 SimBIL_USA    93 USA     BB        USA
 2 KonMCC_USA    80 USA     BB        USA
 3 YaqZHO_CHN    73 CHN     BB        nonUSA
 4 QinZHA_CHN    55 CHN     BB        nonUSA
 5 SunLEE_USA    34 USA     BB        USA
 6 YusOU__CHN    21 CHN     BB        nonUSA
 7 HuaLUO_CHN    18 CHN     BB        nonUSA
 8 UraASH_JPN    13 JPN     BB        nonUSA
 9 SkyBLA_USA    11 USA     BB        USA
10 QiyQIU_CHN     9 CHN     BB        nonUSA
# i 31 more rows
```

**Image 10)**

```
Warning: Removed 1 rows containing missing values (`geom_point()`).
```

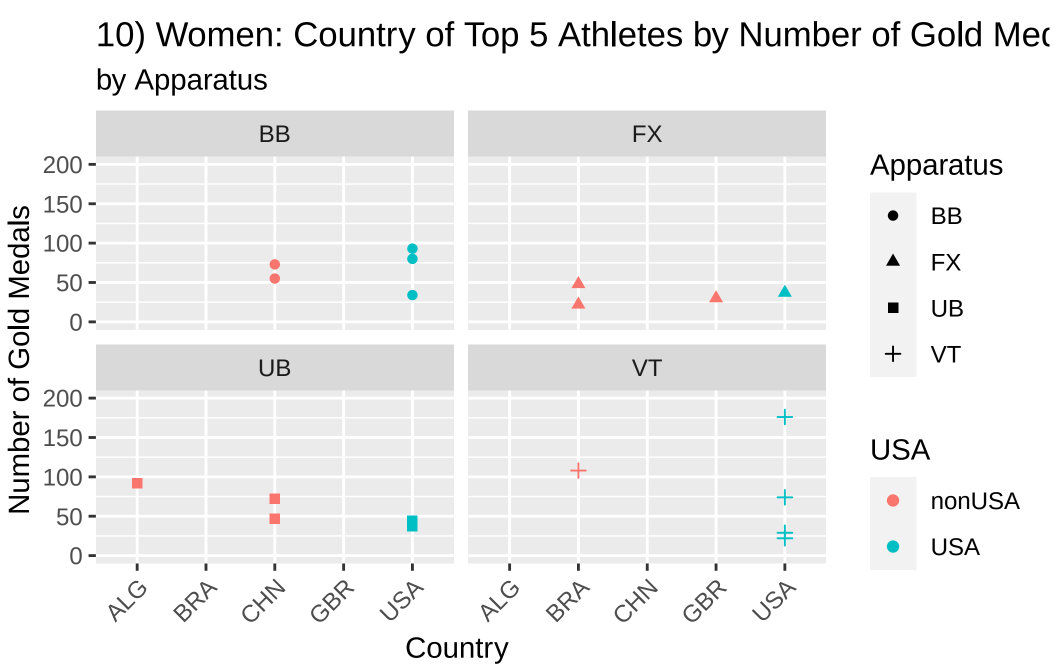


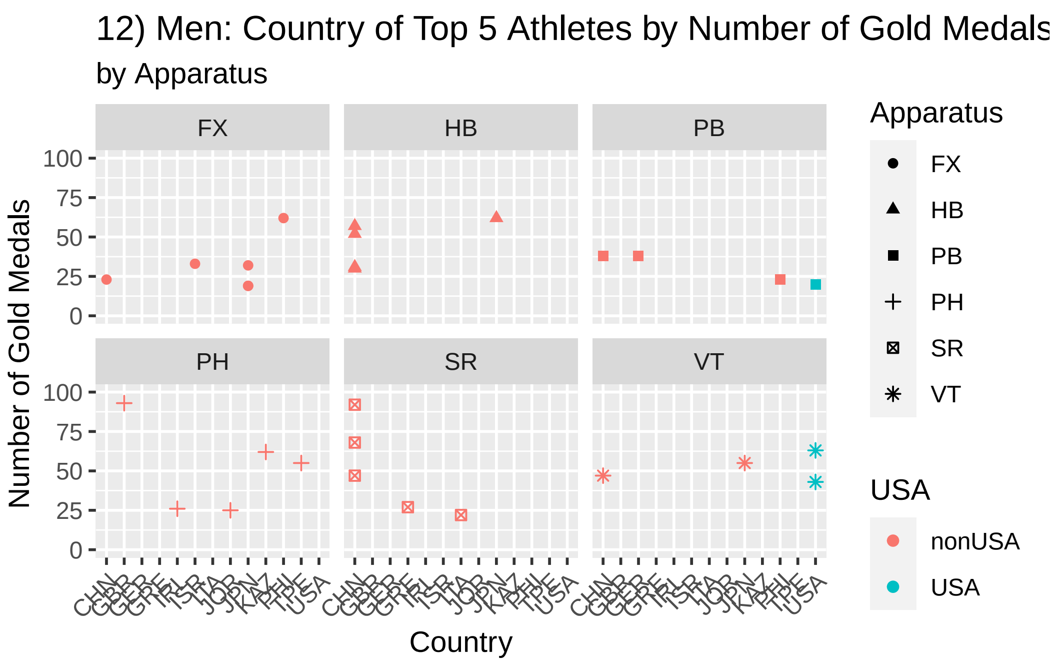

**Image 11)**

```
# A tibble: 61 x 5
# Groups:   Apparatus [6]
   unique_id  Golds Country Apparatus USA
   <chr>      <dbl> <fct>   <chr>     <fct>
 1 CarYUL_PHI    62 PHI     FX        nonUSA
 2 ArtDOL_ISR    33 ISR     FX        nonUSA
 3 RyoDOI_JPN    32 JPN     FX        nonUSA
 4 BohZHA_CHN    23 CHN     FX        nonUSA
 5 DaiHAS_JPN    19 JPN     FX        nonUSA
 6 KazMIN_JPN    19 JPN     FX        nonUSA
```

```
 7 BroMAL_USA    18 USA     FX         USA
 8 PauJUD_USA    17 USA     FX         USA
 9 YulMOL_USA    16 USA     FX         USA
10 GiaREG_GBR    16 GBR     FX         nonUSA
# i 51 more rows
```

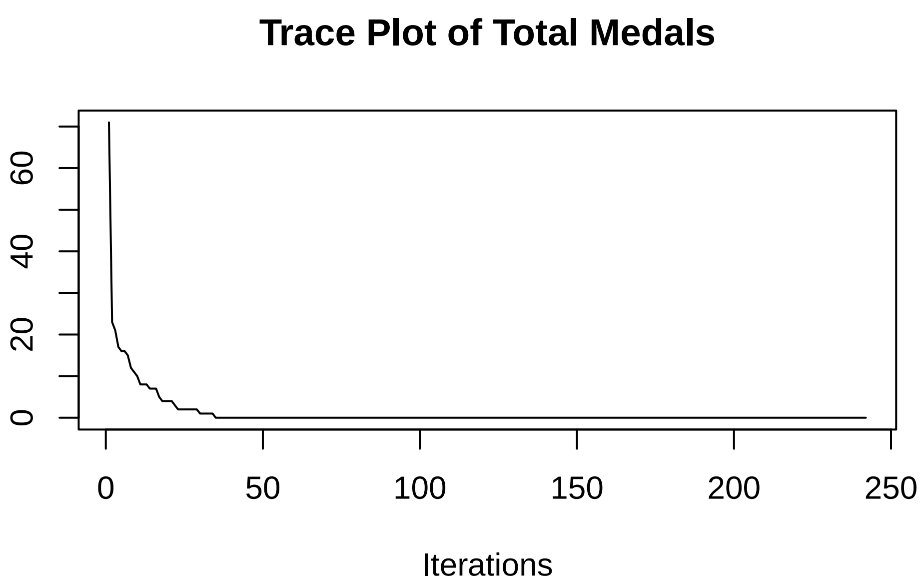
**Image 12)**

```
Warning: Removed 2 rows containing missing values (`geom_point()`).
```

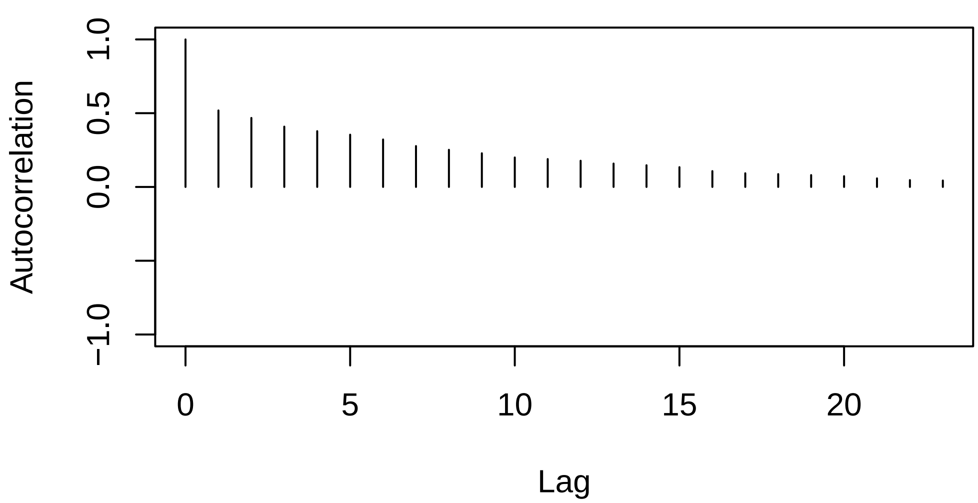


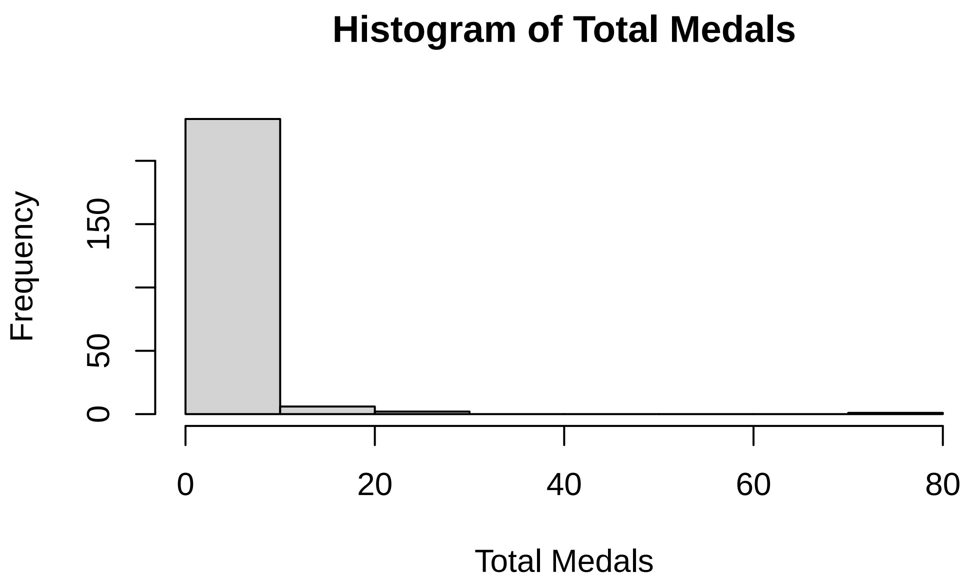

***Note:*** The excessive number of countries display that there is not much overlap in the top 5 most gold medal decorated athletes on the men's team and therefore the lack of well-rounded gymnasts.

**Diagnostics**

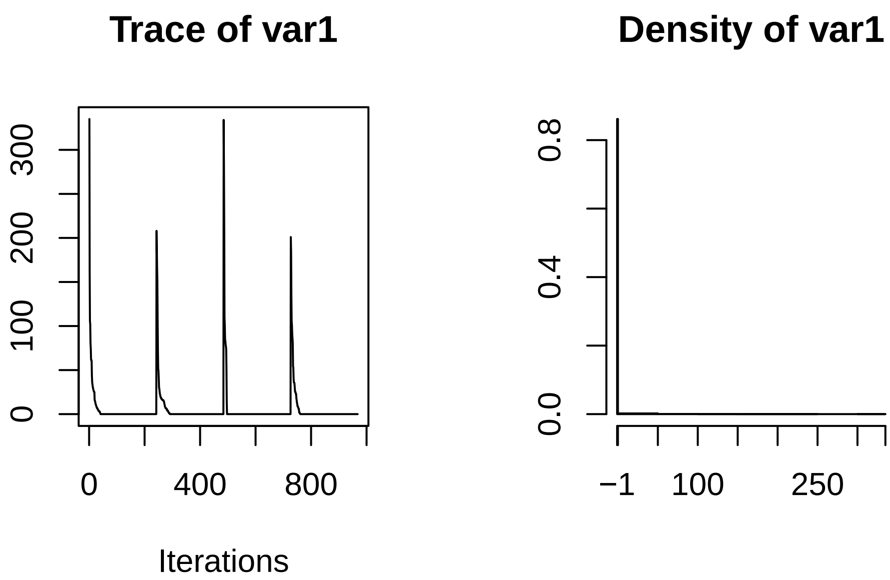


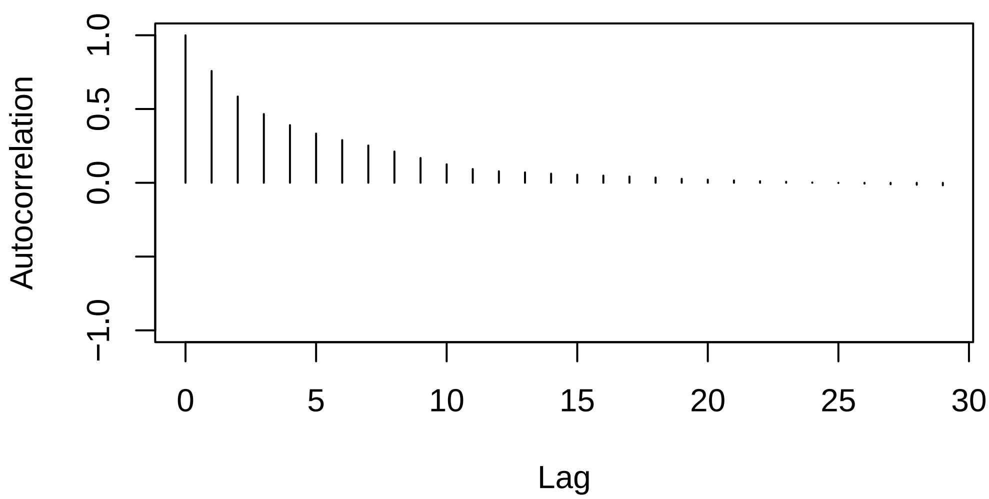

```
     var1
27.00493
```






```
Iterations = 1:968
Thinning interval = 1
Number of chains = 1
Sample size per chain = 968

1. Empirical mean and standard deviation for each variable,
   plus standard error of the mean:

          Mean             SD       Naive SE Time-series SE
        6.1983        28.0299         0.9009         2.4301

2. Quantiles for each variable:

 2.5%   25%   50%   75% 97.5%
 0.00  0.00  0.00  0.00 80.65


     var1
0.1085832


    var1
133.0432
```




```
Iterations = 1:1452
Thinning interval = 1
Number of chains = 1
Sample size per chain = 1452

1. Empirical mean and standard deviation for each variable,
   plus standard error of the mean:

          Mean             SD       Naive SE Time-series SE
        6.1983        22.0044         0.5775         2.1447

2. Quantiles for each variable:

  2.5%    25%    50%    75% 97.5%
```

```
 0.00  0.00  0.00  0.00 64.72
```

```
     var1
0.1295658
```

```
    var1
105.2676
```