Strategizing for Gold: Data Analytics in Selecting USA's 2024 Olympics Gymnastics Team

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1 Introduction

As the 2024 Olympic Games draw near, Team USA stands poised to select its finest athletes in artistic gymnastics who will strive to secure glory for their nation. This analysis aims to find the team of five that maximize the advantages of American gymnastics for both men and women. We first cleaned up the dataset and conducted exploratory data analysis to find patterns, which enables our further examination and team selection through model building and case-by-case analysis. Our final recommendation prioritizes team competition results and incorporates individual results to find a balance, thereby enhancing the prospects for the United States to achieve a distinguished medal tally across all categories.

2 Exploratory Data Analysis

We interacted with our men's and women's data from three perspectives respectively: landscape of frequent competitors in each apparatus, potential associations between D_scores and E_scores, and mean and standard deviations analyses.

We first examined the frequency of appearances by American athletes and noticed the lack of sufficient data entries. Since we cannot create convincing score distributions for individual athletes, we will use the mean and standard deviation as key metrics for further analyses.

2.1 Data Cleaning

As we noticed some athletes' names contain spelling errors or special characters, we compiled a dictionary to fix this issue. Meanwhile, we wrote a function to compile the date value of each competition for later analysis in performance over time and improved readability in other columns. We also reformatted the dataframe to represent each athlete's performance in one row so that it provides both a general sense of performance level and also facilitates our in-depth analysis.

2.2 Male gymnasts

From fitting a linear model, we found that there is a positive association between each individual's average D_scores and E_scores. This suggests that elite athletes can achieve higher scores in both categories. Therefore, we used the total score as the primary metric for subsequent analyses.

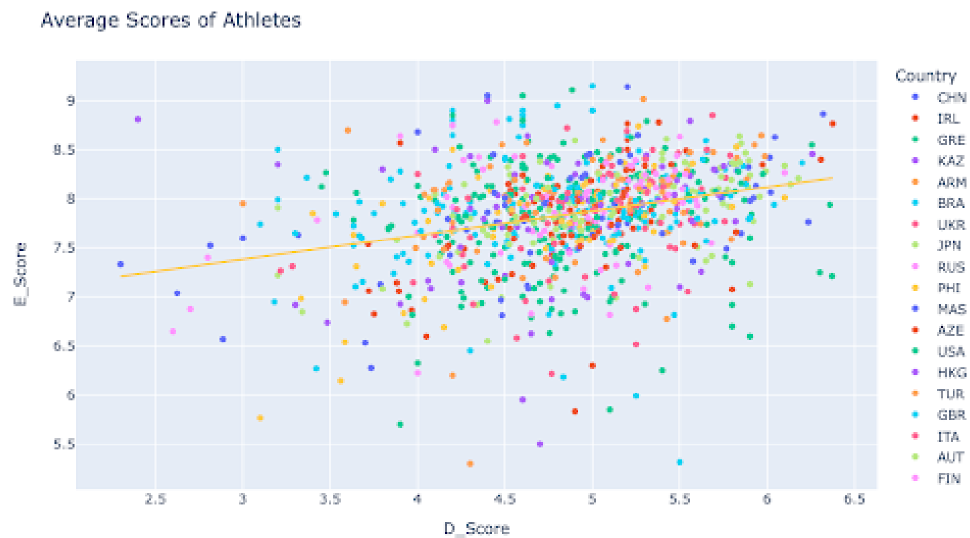

Fig. 1: Men Mean E Scores vs. Mean D Scores

For each men's apparatus, we analyzed them individually to conclude at some patterns. In terms of scoring, only floor exercise and vault are more reliant on *D_score* to distinguish athletes, while the other 4 apparatuses depend more heavily on *E_score*. As for consistency, athletes' performances in horizontal bar, parallel bars, and vault are more stable, while their performances in floor exercise, pommel horse, and still rings are more volatile.

2.3 Female gymnasts

The mean scores for each apparatus across the different competitions also demonstrate a positive association between the difficulty and excellence scores, reinforcing that the female gymnasts who chose more difficult skills made show they were able to complete the routines with delicacy.

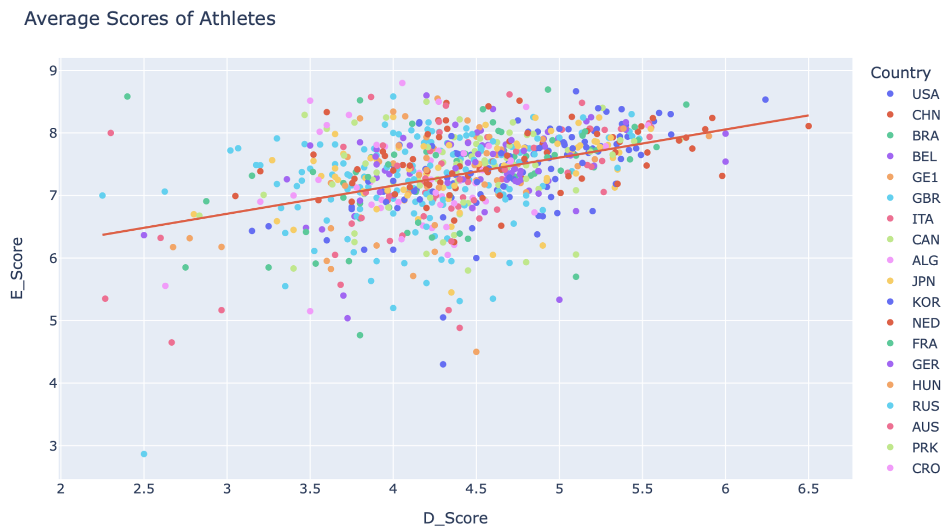

Fig. 2: Women Mean E Scores vs. Mean D Scores

2.4 EDA Summary

We discovered a positive correlation between D_score and E_score, indicating that elite athletes tend to excel in both without the compromising one for the other. Consequently, in our team selection process, greater weight has been placed on assessing their total scores. Additionally, we recognized variances across different apparatuses, which will be carefully considered to accurately evaluate each athlete's prowess on each apparatus.

3 Team Selection Strategy

Based on the preliminary analysis, it appears that the men's and women's teams from the USA are strong contenders in the team competitions. Therefore, our approach is to first put together an optimal team of 5 that maximizes team score, then analyze individual all round and apparatus competitions to find suitable substitutes that make up the final team.

3.1 Modeling Strategies

Given that the average team scores of both men and women teams are well placed in the top 8 teams to qualify, we will primarily focus on selecting athletes that will optimize team scores in the final round.

We are interested in team USA's possibility of earning medals, so we used the following modeling strategies to predict the optimal team's performance for each qualified country to more accurately evaluate team USA's stance in the world.

We attempted two algorithms to select team members that will optimize the total team scores. For countries with fewer numbers of athletes, we enumerated all possible combinations of 5 athletes and selected the team with the highest team score. When there are too many candidates that enumeration becomes computationally exhaustive and impossible, we use a more efficient divided strategy to find the optimal team combinations.

Strategy 1: Enumerate all possible combinations. To find the global maximal score, we enumerated all possible combinations of five athletes and calculated the total score of each combination by summing the top 3 mean scores in the team for each apparatus. For n available athletes in each country, there are nC5 possible combinations and this number rises exponentially. Thus, we cut the pool of athletes to those with mean total scores ranking in top 25 for other countries and 40 for USA. However, this disabled us from considering edge cases: athletes who performed extraordinarily on some apparatus and poorly on the others might be mistakenly cut out. Thus, we came up with an alternative method of building the team.

Strategy 2: Select all-rounded athletes, and add members step-by-step. For the women's team competition, 5 athletes need to compete 12 times in total, while a single athlete can compete in 4 apparatus in the maximum. In the most distributed case, the five athletes can each participate in $[3-3-3-2-2]$ events. In the most focused case, five athletes need to participate in $[4-2-2-2-2]$ events. This means that even in the most averaged case, we will need at least 1 member who participates in at least 3 apparatus. Therefore, we can first select 1 all-rounded athlete who performs best overall on 3 apparatus and then add other athletes one-by-one, by evaluating the total team score after adding each one. This method reduces the computation for n athletes to $k * [(n-1)+(n-2)+(n-3)+(n-4)]$ and so on. Here, k represents the number of computations needed to calculate the group's score with the addition of a new athlete. This is significantly more efficient than the previous approach.

Similarly, in the case of the men's team, we need at least 3 all-rounded athletes, selected based on the best total average score on 4 apparatus. The number of computations is reduced down to $k * [(n-3)+(n-4)]$

However, this stepwise method has a drawback that addition of athletes further down the procedure would interact and affect the score from previous athletes. This means that it is possible that this algorithm will leave out globally maximal combinations that do not seem optimal in intermediate steps.

The alternative method gives the same optimal solution as enumeration for 70% of the time for both men and women. We did not encounter outlier athletes as mentioned before, but this strategy would be helpful to screen for such edge cases if they are present.

3.2 Women's Team Selection

Team Competition Both brute force and optimization algorithms have selected the same result. The five athletes are Simone Biles, Shilese Jones, Konnor McClain, Zoe Miller and Sunisa Lee, having the expected total score of 171.75, ranking first in all teams and far above second place China scoring 166.10, meaning that USA team high hope of winning gold in team competition.

USA's top 5 athletes and their score

	name	FX_mean_score	UB_mean_score	BB_mean_score	VT_mean_score
0	SIMONE BILES	14.87	14.26	14.6	14.98
2	SHILESE JONES	13.7	14.51	0.0	14.29
3	KONNOR MCCLAIN	13.63	0.0	14.5	14.28
56	ZOE MILLER	0.0	14.01	0.0	0.0
618	SUNISA LEE	0.0	0.0	14.12	0.0

USA's score sum is: 171.75

Fig. 3: Team-Score Optimized USA Women's Team

Individual All-Round Competition To simulate the expected all-round score, we added up each athlete's mean score in all apparatus and ranked them.

	counrty	team_score
2	CHN	166.10
4	ITA	164.06
3	BRA	163.70
0	GBR	163.37
7	JPN	161.13
6	FRA	159.86
1	CAN	159.34
5	NED	158.79
10	KOR	156.63
9	ROU	155.80
8	AUS	155.61

Fig. 4: Team Score Ranking of Other 11 Competing Women's Team

	name	Country	Standardized_Score_Sum	Rank
0	SIMONE BILES	USA	58.71	1.0
1	REBECA ANDRADE	BRA	56.60	2.0
2	SHILESE JONES	USA	55.82	3.0
3	KONNOR MCCLAIN	USA	55.68	4.0
4	JESSICA ROSE GADIROVA	GBR	54.67	5.0
5	SKYE BLAKELY	USA	54.54	6.0
6	JORDAN CHILES	USA	54.51	7.0
7	JADE CAREY	USA	54.38	8.0
8	ALICE D AMATO	ITA	54.36	9.0
9	LEANNE WONG	USA	54.28	10.5

Fig. 5: Women's All-round Ranking

We observe that among top 10 athletes, USA occupies 7, with Simone Biles ranking first and leading 2nd place Rebeca Andrade by 2.11 points. We predict that the USA would win gold and bronze in the individual all-round. The top 3 individuals from the USA are already on our team, and no other athletes seem to be able to surpass Rebaca and win another medal for Team USA. Hence, individual all-round performance alone is not convincing enough to make any substitutions.

Apparatus Analysis

Floor Exercise Simone Biles ranks 1st in FX, averaging a score of 14.87 and leading by 0.66, who's expected to win gold. For other USA athletes, Kaliya Lincoln ranks 4th and is only 0.09 point behind 3rd place Jessica, meaning that she has a decent chance of winning a medal and should be considered as a potential substitution.

	name	Country	FX_mean_score	FX_std	FX_count
0	SIMONE BILES	USA	14.87	0.32	7.0
1	REBECA ANDRADE	BRA	14.21	0.30	8.0
4	JESSICA ROSE GADIROVA	GBR	14.10	0.35	14.0
43	KALIYA LINCOLN	USA	14.01	0.28	6.0
7	JADE CAREY	USA	13.80	0.39	8.0
17	MARTINA MAGGIO	ITA	13.77	0.19	7.0
6	JORDAN CHILES	USA	13.73	0.34	11.0
2	SHILESE JONES	USA	13.70	0.42	14.0
13	KAYLA DICELLO	USA	13.62	0.22	8.0
119	SABRINA MANECA VOINEA	ROU	13.59	0.18	6.0

Fig. 6: Women's FX Ranking

Balance Beam Simone Biles is again the leading figure. She scores on average 14.60, 0.63 points higher than 2nd place Yushan and would secure the gold medal. However, there are no other USA athletes that may compete in this apparatus.

	name	Country	BB_mean_score	BB_std	BB_count
0	SIMONE BILES	USA	14.60	0.22	7.0
11	YUSHAN OU	CHN	13.97	0.40	9.0
50	QINGYING ZHANG	CHN	13.90	0.71	5.0
53	MANA OKAMURA	JPN	13.81	0.30	5.0
627	URARA ASHIKAWA	JPN	13.81	0.40	5.0
726	SANNE WEVERS	NED	13.60	0.44	5.0
38	JIN ZHANG	CHN	13.55	0.45	7.0
1	REBECA ANDRADE	BRA	13.50	0.51	10.0
5	SKYE BLAKELY	USA	13.46	0.67	11.0
10	FLAVIA SARAIVA	BRA	13.45	0.87	8.0

Fig. 7: Women's BB Ranking

Uneven Bars The top 3 athletes worldwide have very small gaps. USA athlete Shilese ranks 2nd, 0.03 point behind 1st place Xiaoyuan and 0.02 point above 3rd place Qiyuan. Shilese has a much more stable performance than others shown by standard deviation, giving her a proper chance of competing for a gold medal, but it is not guaranteed.

	name	Country	UB_mean_score	UB_std	UB_count
32	XIAOYUAN WEI	CHN	14.54	0.69	6.0
2	SHILESE JONES	USA	14.51	0.49	15.0
16	QIYUAN QIU	CHN	14.49	1.03	10.0
0	SIMONE BILES	USA	14.26	0.18	7.0
1	REBECA ANDRADE	BRA	14.23	0.56	11.0
8	ALICE D AMATO	ITA	14.20	0.58	16.0
57	REBECCA DOWNIE	GBR	14.16	0.32	5.0
621	GIORGIA VILLA	ITA	14.11	0.10	11.0
499	ELISABETH SEITZ	GER	14.05	0.75	9.0
56	ZOE MILLER	USA	14.01	1.26	9.0

Fig. 8: Women's UB Ranking

Vault Simone Biles aces in women's vault, scoring 14.98 on average and leads by 0.32 points, having a great chance of winning another gold. 5 out of top 6 athletes in vault are American, and the question again comes down to who has the chance of winning more medals for the USA by surpassing 2nd place Rebeca. 3rd place Jade Carey scores only 0.16 points behind Rebeca and she has a much lower standard deviation (0.28 vs 0.93) and should be considered for substitution.

	name	Country	VT_mean_score	VT_std	VT_count
0	SIMONE BILES	USA	14.98	0.41	9.0
1	REBECA ANDRADE	BRA	14.66	0.93	15.0
7	JADE CAREY	USA	14.50	0.28	15.0
2	SHILESE JONES	USA	14.29	0.18	11.0
6	JORDAN CHILES	USA	14.22	0.22	19.0
5	SKYE BLAKELY	USA	14.15	0.20	6.0
20	ONDINE ACHAMPONG	GBR	14.15	0.20	11.0
25	TIANA SUMANASEKERA	USA	14.12	0.11	6.0
47	SEOJEONG YEO	KOR	14.09	0.48	17.0
8	ALICE D AMATO	ITA	14.06	0.18	10.0

Fig. 9: Women's VT Ranking

Final Women's Team Selection After analyzing all six competitions, the two potential changes we might make to our team selection is Kaliya Lincoln and Jade Carey for their chance of winning medals in FX and VT respectively. There are also two subjects to substitute in our original team selection: Zoe Miller and Susina Lee, both of whom are not contenders for any medals. Examining the impact of making both substitutions on the team result, the result is as follows:

	name	FX_mean_score	BB_mean_score	UB_mean_score	VT_mean_score
0	SIMONE BILES	14.87	14.6	14.26	14.98
7	JADE CAREY	13.8	0.0	0.0	14.5
2	SHILESE JONES	0.0	13.32	14.51	14.29
3	KONNOR MCCLAIN	0.0	14.5	13.27	0.0
43	KALIYA LINCOLN	14.01	0.0	0.0	0.0

Total Score: 170.91

Fig. 10: Women's Final Selection

The expected total score dropped 0.84 points to 170.91, which still leads any other team by a large margin and should still win the gold team medal. Thus, both of these substitutions should be made for adding the chance of winning 2 extra apparatus medals.

Team Competition Expectation for New Team Selection

In conclusion, the final USA women's team selection is Simone Biles, Shilese Jones, Konnor McClain, Jade Carey, and Kaliya Lincoln. This team has a promising future of winning the team gold medal, in addition to the gold medals of individual's all-round, FX, BB, and VT. Moreover, In floor exercise, an additional bronze or silver is within reach, and in UB, prospects look bright for at least a bronze or silver medal. Finally, there's a realistic possibility that the team could dominate the VT event, potentially sweeping all three medals – gold, silver, and bronze.

3.3 Men's Team Selection

Team Competition Similarly, we first decide an optimized group for the USA men's team that maximizes team score. Two algorithms again yield the same result: Paul Juda, Asher Hong, Brody Malone, Vitaliy Guimaraes, and Yul Moldauer, scoring 254.9 in team competition. This result ranks 3rd among all qualified countries, far behind second place Japan by 4.54 points and also above the 4th place Great Britain by 2.86 points. Thus, the USA men's team has no chance of winning gold, but a big chance of winning bronze in team competition.

	name	FX_mean_score	HB_mean_score	PB_mean_score	PH_mean_score	SR_mean_score	VT_mean_score
9	PAUL JUDA	14.34	13.92	0.0	13.45	0.0	14.5
23	ASHER HONG	0.0	0.0	14.61	0.0	14.15	14.49
5	BRODY MALONE	0.0	14.37	14.5	13.65	13.87	14.47
7	VITALIY GUIMARAES	14.25	13.4	0.0	14.35	0.0	0.0
21	YUL MOLDAUER	14.07	0.0	14.54	0.0	13.97	0.0

Total Score: 254.9

Fig. 11: Team-Score Optimized USA Men's Team

	counrty	team_score
0	CHN	260.83
1	JPN	259.47
2	GBR	252.04
8	TUR	249.08
10	UKR	247.65
5	ITA	247.21
6	SUI	245.88
4	GER	245.80
3	CAN	244.17
7	ESP	243.68
9	NED	242.13

Fig. 12: Team Score Ranking of Other 11 Competing Men's Team

Individual All-Round Competition The best American athlete is Brody Malone, who ranks 6th and scores 84.57. There is little chance of competing for gold, but Brody may have a chance of getting into top 3 with the score different being only 0.7. However, no other American athletes stand a chance of winning something in all-round competition.

	name	Country	Standardized_Score_Sum	Rank
0	BOHENG ZHANG	CHN	86.56	1.0
1	KAZUMA KAYA	JPN	85.41	2.0
2	WATARU TANIGAWA	JPN	85.27	3.0
3	CONG SHI	CHN	84.97	4.0
4	DAIKI HASHIMOTO	JPN	84.66	5.0
5	BRODY MALONE	USA	84.57	6.0
6	CARLOS YULO	PHI	83.96	7.0
7	VITALIY GUIMARAES	USA	83.95	8.0
8	KAKERU TANIGAWA	JPN	83.79	9.0
9	PAUL JUDA	USA	83.75	10.0

Fig. 13: Men's All-round Ranking

Apparatus Analysis

Floor Exercise Paul Juda is the only American athlete in the top 4, ranking 4th and only 0.09 point behind 3rd place and 0.22 point behind 1st. There is a decent chance of winning a medal, or even gold, for Paul Juda, but he is also the only American athlete having a chance.

	name	Country	FX_mean_score	FX_std	FX_count
16	RYOSUKE DOI	JPN	14.56	0.27	5.0
6	CARLOS YULO	PHI	14.51	0.76	13.0
0	BOHENG ZHANG	CHN	14.43	0.26	8.0
9	PAUL JUDA	USA	14.34	0.34	6.0
747	KAZUKI MINAMI	JPN	14.31	0.40	7.0
8	KAKERU TANIGAWA	JPN	14.27	0.19	4.0
36	ARTEM DOLGOPYAT	ISR	14.27	1.04	23.0
4	DAIKI HASHIMOTO	JPN	14.26	0.50	10.0
27	JAKE JARMAN	GBR	14.21	0.48	19.0
538	HANSOL KIM	KOR	14.21	0.58	6.0

Fig. 14: Men's FX Ranking

Horizontal Bars Brody Malone ranks 3rd among all, who is 0.26 point behind 1st place Daiki, but also has a horde of other elite athletes chasing behind him with minuscule margins. Due to the high standard deviation in this apparatus, it's hard to predict where Brody Malone will end up on the table. He has a chance of winning gold, but he might also drop out of the top 3. No other American athletes can be taken into consideration.

	name	Country	HB_mean_score	HB_std	HB_count
4	DAIKI HASHIMOTO	JPN	14.63	0.59	11.0
0	BOHENG ZHANG	CHN	14.52	0.71	9.0
5	BRODY MALONE	USA	14.37	0.58	13.0
12	WEI SUN	CHN	14.31	0.48	6.0
391	CHAOPAN LIN	CHN	14.31	0.33	5.0
3	CONG SHI	CHN	14.31	0.76	5.0
624	YUYA KAMOTO	JPN	14.24	0.12	5.0
28	SHOHEI KAWAKAMI	JPN	14.23	0.35	6.0
1	KAZUMA KAYA	JPN	14.08	0.08	6.0
856	TIN SRBIC	CRO	13.99	0.45	20.0

Fig. 15: Men's HB Ranking

Parallel Bars The highest ranking American is Curran Philips, who stands on 10th position in parallel bars and is 0.34 points behind 3rd place Carlos Yulo.

	name	Country	PB_mean_score	PB_std	PB_count
618	JINGYUAN ZOU	CHN	15.92	0.16	7.0
35	LUKAS DAUSER	GER	15.15	0.57	10.0
6	CARLOS YULO	PHI	15.08	0.29	14.0
0	BOHENG ZHANG	CHN	15.02	0.53	8.0
15	ILLIA KOVTUN	UKR	14.98	0.29	30.0
533	KAITO SUGIMOTO	JPN	14.95	0.13	5.0
397	DEHANG YIN	CHN	14.88	0.17	4.0
2	WATARU TANIGAWA	JPN	14.86	0.07	4.0
3	CONG SHI	CHN	14.84	0.16	5.0
626	CURRAN PHILLIPS	USA	14.74	0.78	15.0

Fig. 16: Men's PB Ranking

After closely examining the score records of Curran, we notice that mean score alone cannot reflect his performance. The histogram below shows that there are multiple instances where he scores above 15.3 and his highest record is 15.55. It means that when he performs well, he may even get into the top 3 but cannot challenge for gold, but his inconsistency is still lethal. Also, he only competes in 2 apparatus so his contribution would be very limited.

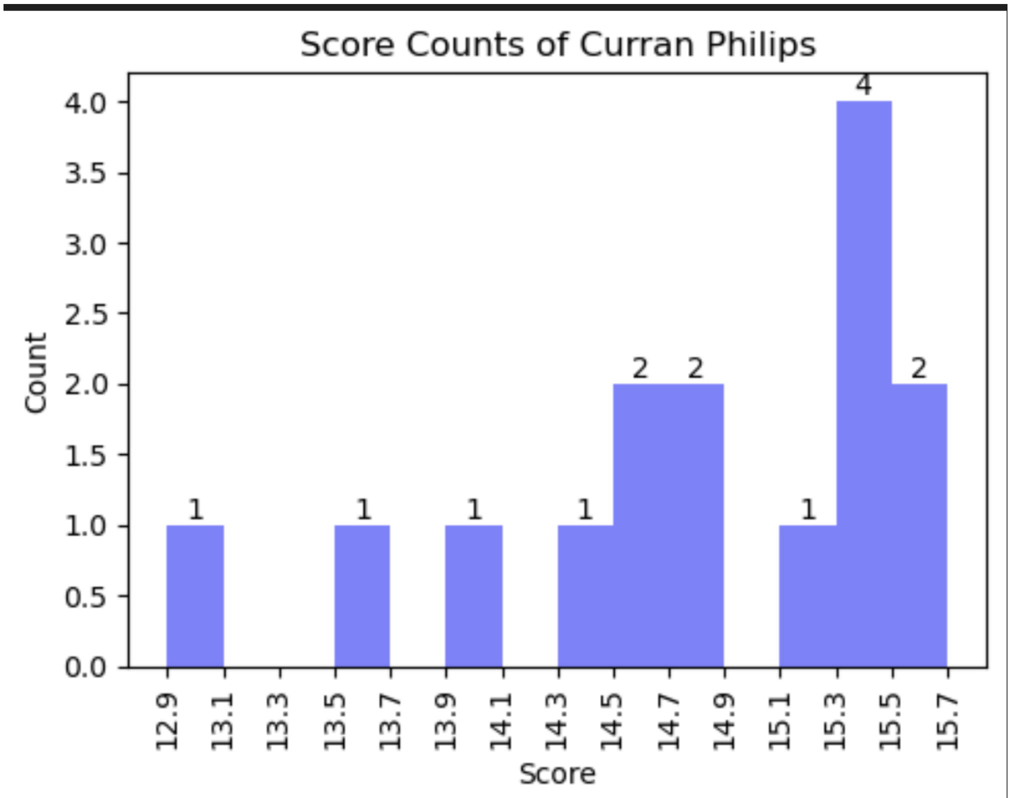

Fig. 17: Curran Analysis

Pommel Horse In Pommel Horse, Stephen Nedoroscik is the only American athlete on the table, ranking 9th. He is 0.41 points behind 3rd place Rhys and needs a closer examination to determine his chance of winning medal.

	name	Country	PH_mean_score	PH_std	PH_count
837	MC RHYS CLENAGHAN	IRL	15.14	0.16	4.0
628	RYOTA TSUMURA	JPN	14.88	0.43	6.0
840	RHYS MCCLENAGHAN	IRL	14.71	0.38	16.0
839	NARIMAN KURBANOV	KAZ	14.71	0.69	31.0
48	CHIH KAI LEE	TPE	14.49	0.88	15.0
844	HARUTYUN MERDINYAN	ARM	14.42	0.48	15.0
1	KAZUMA KAYA	JPN	14.37	0.21	7.0
453	YU JAN SHIAO	TPE	14.33	0.62	18.0
847	STEPHEN NEDOROSCIK	USA	14.30	0.69	12.0
397	DEHANG YIN	CHN	14.29	0.35	6.0

Fig. 18: Men's PH Ranking

Stephen's performance is again inconsistent. His highest achievement is 15.2 points, and there is no clear pattern of the distribution of his scores. When he is at his best, he could even contend for gold medal, but his average performance is not enough to win anything.

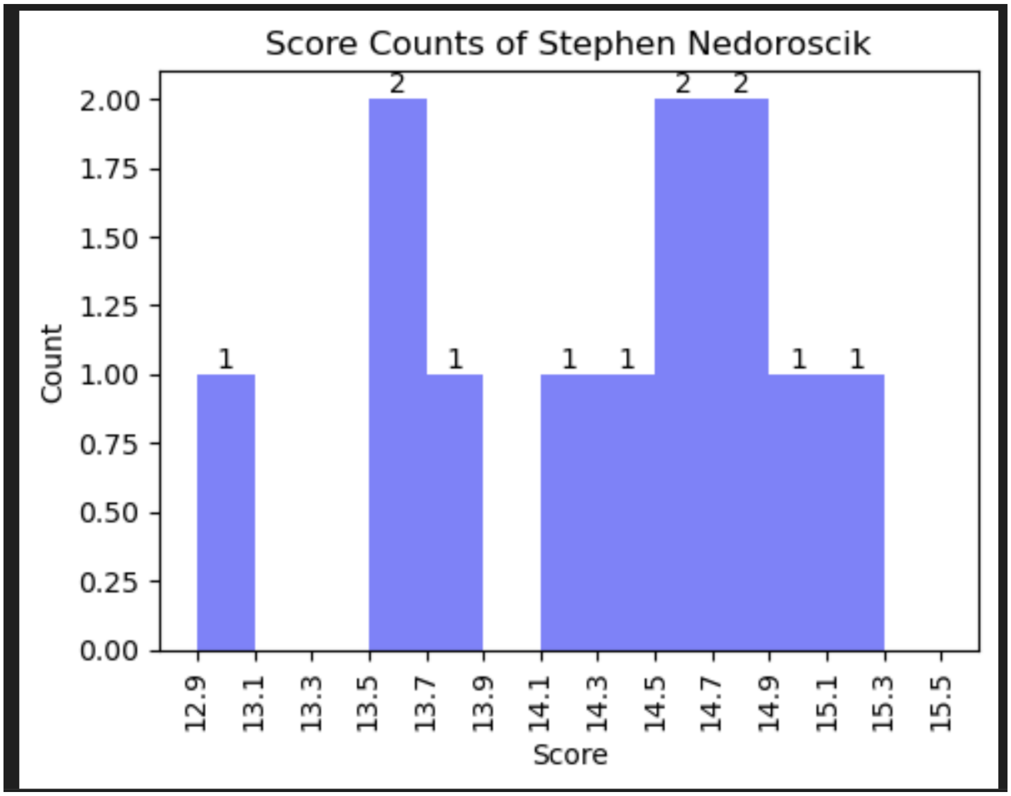

Fig. 19: Stephen Analysis

Still Rings In still rings, no American athlete is capable of contending for a medal.

	name	Country	SR_mean_score	SR_std	SR_count
635	YANG LIU	CHN	15.23	0.14	5.0
13	XINGYU LAN	CHN	15.11	0.29	9.0
618	JINGYUAN ZOU	CHN	14.80	0.32	7.0
838	ELEFTHERIOS PETROUNIAS	GRE	14.80	0.39	9.0
17	ADEM ASIL	TUR	14.78	0.27	27.0
541	HAO YOU	CHN	14.73	0.12	6.0
650	SALVATORE MARESCA	ITA	14.71	0.08	6.0
841	VAHAGN DAVTYAN	ARM	14.61	0.14	18.0
552	IBRAHIM COLAK	TUR	14.60	0.34	15.0
629	MARCO LODADIO	ITA	14.60	0.07	4.0

Fig. 20: Men's SR Ranking

Vault For vault, the only American athlete considered is Khoi Young. The gap between top athletes in vault is very small, as Khoi is only 0.2 point behind 1st place Artur and there are a handful of others in the same range. Thus, Khoi may end up at any position from winning gold to nothing.

	name	Country	VT_mean_score	VT_std	VT_count
26	ARTUR DAVTYAN	ARM	14.89	0.36	50.0
187	NAZAR CHEPURNYI	UKR	14.79	0.16	30.0
27	JAKE JARMAN	GBR	14.76	0.50	42.0
6	CARLOS YULO	PHI	14.69	0.40	25.0
19	KHOI YOUNG	USA	14.69	0.30	15.0
633	IGOR RADIVILOV	UKR	14.68	0.37	33.0
2	WATARU TANIGAWA	JPN	14.65	0.44	11.0
4	DAIKI HASHIMOTO	JPN	14.64	0.40	7.0
747	KAZUKI MINAMI	JPN	14.58	0.34	10.0

Fig. 21: Men's VT Ranking

Final Men's Team Selection Based on previous analysis, 3 other athletes may be considered for substitutions: Curran Philips for PB, Stephen Nedoroscik for PH, and Khoi Young for VT. Among the original team, Paul Juda and Brody Malone both made significant contributions and have a chance of winning an apparatus medal, so they should not be substituted. Therefore, we simply determine 3 spots from 6 athletes and find a balance between competitions. Running another combination algorithm, the important results are as follows:

To optimize team score, our team selection remains the same. They are more likely to secure a bronze medal in team competition, but only have a chance of winning two apparatus medals: FX and HB.

To maximize the amount of medal contenders, we would make all three substitutions into our team, making the final team Paul Juda, Brody Malone, Stephen Nedoroscik, Curran Phillips, and Khoi Young. The team total score drops down to 253.27, only 1.23 points ahead of GBR. It would shrink the chance of winning the bronze medal in team competition, but they may compete for 5 apparatus medals in total, adding in Khoi Young who has a chance for gold in VT, Curran Phillips who contend for silver in PB, and Stephen Nedoroscik who would aim for a medal in PH.

To find a balance, we will keep Vitaliy Guimaraes and sub in Khoi Young and Curran Phillips. The team score would only drop down to 254.42, which is still 2.38 points ahead of GBR, and make the bronze team medal rather secured. The inclusion of Khoi and Curran also adds hope for two extra apparatus medals.

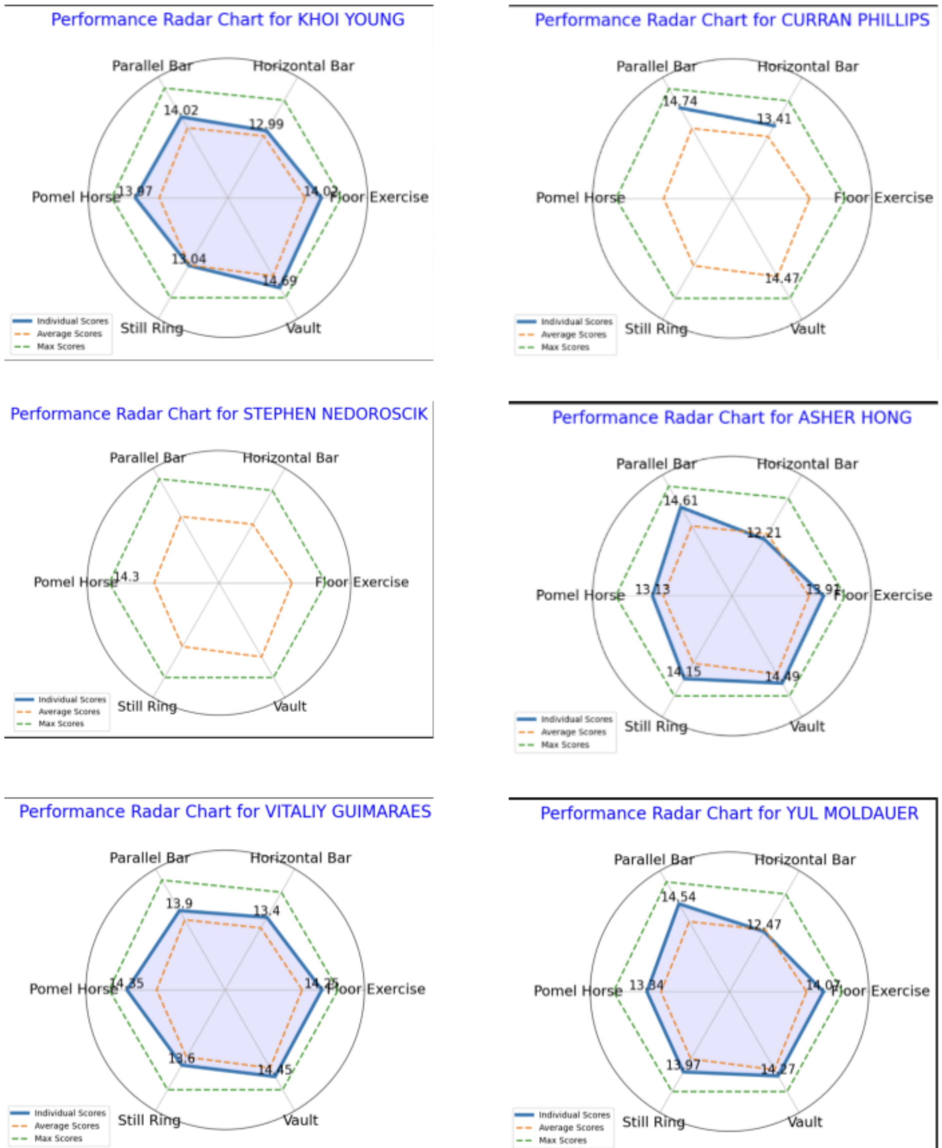

Fig. 22: Radar Charts

	name	FX_mean_score	PB_mean_score	HB_mean_score	PH_mean_score	SR_mean_score	VT_mean_score
2	KHOI YOUNG	14.02	14.02	0.0	13.97	13.04	14.69
1	PAUL JUDA	14.34	0.0	13.92	0.0	13.75	14.5
0	BRODY MALONE	13.71	14.5	14.37	13.65	13.87	14.47
3	CURRAN PHILLIPS	0.0	14.74	13.41	0.0	0.0	0.0
4	STEPHEN NEDOROSCIK	0.0	0.0	0.0	14.3	0.0	0.0

Total Score: 253.27

Fig. 23: Men's Final Selection - Prioritize Medal Count

	name	FX_mean_score	PB_mean_score	HB_mean_score	PH_mean_score	SR_mean_score	VT_mean_score
3	KHOI YOUNG	14.02	14.02	0.0	13.97	0.0	14.69
1	PAUL JUDA	14.34	0.0	13.92	0.0	13.75	14.5
0	BRODY MALONE	0.0	14.5	14.37	13.65	13.87	14.47
4	CURRAN PHILLIPS	0.0	14.74	13.41	0.0	0.0	0.0
2	VITALIY GUIMARAES	14.25	0.0	0.0	14.35	13.6	0.0

Total Score: 254.42

Fig. 24: Men's Final Selection - Balanced

In summary, it is hard to decide one best team for the USA men's team like we did for women's as two extra factors should be considered beyond this research. One is to determine their real chance of winning medals in their respective apparatus with more training data and resources, as we currently are unable to quantify their probability of winning medals. Another is Team USA's strategy: whether they prioritize team medal or medal count determines the final team composition. Our analysis provided three options on this spectrum, and all three are a reasonable team worthy of representing the highest level of team USA.

4 Limitations and Future Directions

Our analyses, while uncovering many insights in the performance of athletes, should be understood within the context of certain limitations. For one, it's not entirely realistic to generalize previous performances to predict new ones. Athletes evolve over time, influenced by factors such as health conditions, injuries, and aging, which our model does not account for. In reality, the performance of gymnasts is more reliant on training data, which are abundant and more reflective of real distributions. Future research could benefit from incorporating these data points [1]. Advanced technologies like E-score video analyses [2], as well as nano track accelerometers providing information on workload and intensity [3], could also be utilized to enhance our understanding of gymnastics performances. Moving forward, incorporating the following factors into our analysis could also provide valuable insights:

- Identify alternate members in case they become injured, based on maximization of team scores and competitiveness on individual apparatus.
- Follow live updates on the team selection of other countries as they are announced.
- Understand stability and stress management of athletes in different sized tournaments, and changes in performance as they attempt more difficult moves.
- Analyze the psychological impact of having elite "GOAT" athletes in the team and the training stress involved. [4]
- Explore the strategy where some athletes focus on achieving stable scores, while others strive for high scores, taking on more risk.

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