

An Investigation of Inequity on *Big Brother*: Diving into Disparities on the Hit Reality Show

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Abstract

Big Brother is a CBS reality competition show that sees a group of contestants enter a house under 24/7 surveillance, periodically voting each other off until one winner remains. The program has repeatedly been criticized for biases held by both players and production, as evidenced by factors including a lack of diversity in casting, unfair competition design, and noteworthy bigotry scandals over its 25-season run. This analysis uses ordinal regression to study potential associations between demographic factors and one's performance on *Big Brother*, aiming to uncover whether or not the show is equitable for all contestants. Model results find that men have significantly higher odds than women of being top competition performers on their season; additionally, BIPOC contestants had lower odds than non-BIPOC of advancing further in the game, but this disparity is being mitigated by a 2020 network initiative requiring increased racial and ethnic diversity in casting.

1 Introduction

Based on George Orwell’s dystopian novel *1984*, *Big Brother* is a hit reality television competition that sees a group of contestants enter a house with 24/7 audio and video surveillance. Originally created by John de Mol and launched in the Netherlands in 1999, the show followed twelve players, known as “houseguests”, on a 106-day journey where the viewers would periodically vote to “evict” one of them, eliminating them from the competition; when the series was not airing, audiences could view the houseguests’ every move via an online livestream. The show came to the United States a year later with the same format, but disappointing ratings for *Big Brother 1* led to a massive shift in approach. From *Big Brother 2* to the most recent installation *Big Brother 25*, the show has given the power to the houseguests, forcing them to evict each other and adding a power struggle component to the fascinating social experiment.

Over the years, *Big Brother* has repeatedly made headlines for problematic behaviors exhibited by both the cast members and production. In 2013, racist and homophobic remarks made by several houseguests on *Big Brother 15* made national news (Chan 2013), leading to contestants losing employment and facing extensive backlash from the public (Hines 2013). Additionally, the show has historically been scrutinized for a lack of diversity in casting, underscored by the fact that the program produced zero Black winners in its first 22 seasons. Most recently, *Big Brother 25* frustrated audiences as female houseguests won a measly 6 out of 31 weekly competitions; production was also accused of not making proper accommodations for their first deaf houseguest (Siwak 2023). Fortunately, CBS, the network on which *Big Brother* airs, has taken steps to counteract this history of inequity, namely by launching an initiative to make all reality show casts at least 50% Black, Indigenous, People of Color (Whitten 2020).

This project will examine the potential influence of certain demographic factors on how a houseguest fares on *Big Brother*, aiming to discover if the program has been equitable for past contestants. Two metrics of performance will be investigated: how a houseguest places on a season (1st, 2nd, 3rd, etc.), and the number of competitions a houseguest wins on their season. How the relationships of demographic factors with performance change over time will also be studied as a means of measuring both the effectiveness of network initiatives and general societal shifts.

2 Methodology

2.1 Data

The bulk of the data for this project comes from a dataset created by Vince Dixon as a part of their 2019 data visualization project on diversity in *Big Brother* (Dixon 2019). Dixon gathered both demographic and performance data on contestants from the first 23 seasons; since there had been no updates made since early 2022, I manually entered the same data for houseguests from *Big Brother 24* and *Big Brother 25*, using the Big Brother Wiki for reference (“The Big Brother Wiki,” n.d.). The resultant dataset contains 357 rows, one for each contestant from the show’s second to its twenty-fifth season (houseguests from *Big Brother 1* are omitted due to the show’s different format, involving audience evictions and no weekly power competitions). While Dixon’s original dataset contained 49 variables, this was reduced to 17 through both the removal of unneeded columns and the creation of new ones. Data wrangling and cleaning was conducted in both Google Sheets and R.

Variables of note for this project include the following (where a hashtag indicates the variable was not in the original Dixon dataset):

- Age: Numeric variable indicating age of the houseguest at time of filming
- Gender: Binary indicator of the gender of the houseguest at time of filming (1 = Male, 0 = Female). Note that *Big Brother* has never cast an individual who is openly neither male nor female, but contestants have come out as non-binary after the show.
- BIPOC#: Binary indicator on whether or not the houseguest is Black, Indigenous, and/or a Person of Color (1 = Yes, 0 = No).
- LGBT#: Binary indicator on whether or not the houseguest identified as part of the LGBT community at time of filming (1 = Yes, 0 = No).
- Season Code: Numeric variable indicating the season that the houseguest participated in.
- Placement Bucket#: Ordinal variable indicating how well a houseguest placed on their season. The five levels are “Early Out”, “Lower Middle”, “Upper Middle”, “Late Game”, and “Winner”; these each encompass one quarter of the houseguests on each season, except for the fourth quarter which is split into “Late Game” and “Winner”.
- Wins Bucket#: Ordinal variable indicating how many competitions a houseguest won on their season, relative to the other houseguests. If multiple houseguests won the same number of competitions, those who were evicted earlier will receive a better

rank as they had less opportunities to win competitions. The four levels are “Bottom Quartile”, “Low Quartile”, “High Quartile”, and “Top Quartile”; these each encompass one quarter of the houseguests on each season.

The response variables for this project will be placement bucket and wins bucket. The decision to define a houseguest’s placement and competition performance as relative to the other contestants on their season is to account for the fact that different seasons have different amounts of houseguests and competitions; for example, winning 2 competitions on a 10-week season is not identical to winning 2 competitions on a 14-week season.

2.2 Exploratory Data Analysis

To visualize potential disparities in performance on *Big Brother* across demographic groups, I conducted exploratory data analysis on the 357 houseguests.

2.2.1 Placement

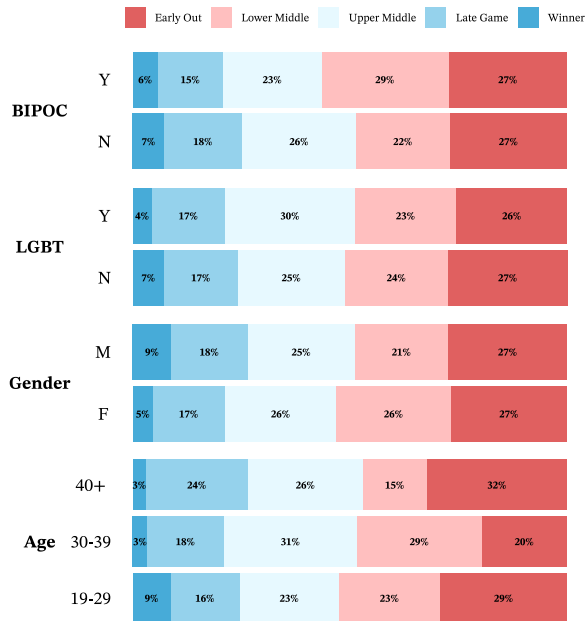


Figure 1: Breakdown of placement by demographic group

Figure 1 displays the breakdown of *Big Brother* placement by BIPOC status, LGBT status, gender, and age group; in a scenario with perfect equity, all bars (except Late Game and Winner, which would need to be added together) would be at 25%.

For *LGBT status*, there does not seem to be a major disparity between queer and non-queer houseguests when it comes to making the upper middle portion of the game

(51% for LGBT, 49% for non-LGBT); however, the proportion of non-LGBT houseguests who go on to win the game is almost double the proportion for LGBT houseguests (7% vs 4%). There have only been two openly queer winners of *Big Brother*: Andy Herren in season 15, and Kaycee Clark in season 20. Fortunately, queer representation on the show appears to be on the rise, with the three most recent seasons topping the list for most LGBT houseguests (3 in season 24, and 4 in seasons 23 and 25).

For *gender*, men have historically dominated the winners circle, taking the title in 17 out of 25 seasons of *Big Brother*; unfortunately, this trend does not seem to be on the decline, with only one woman winning in the five most recent seasons. The proportion of women making it to the late-game stage in general is also noticeably lower than it is for men (22% vs 27%); potential explanations for this could include the historical failure of women’s alliances, implicit/explicit biases on the basis of gender, or competition design that favors men (which will be touched upon later).

For *age*, houseguests in their thirties and beyond have historically had trouble clinching the win; the proportion of 19-29 year olds who earn the prize is triple that of the other age groups. This makes intuitive sense, as *Big Brother* casting has always skewed younger (median = 27, median = 29.1) and alliances tend to be formed on the basis of similarities. Despite this, though, houseguests above the age of 40 actually make the late game at a higher rate than the other age groups; on the flip side, their rate for being an early out is also the highest. There are two stereotypical outcomes for older houseguests on *Big Brother*: evicted first, likely due to not fitting in well with the group (like Jodi Rollins on season 14 or Steve Arienta on season 20), or taken to the end, likely due to not being seen as a threat (like Kevin Schlehber on season 19 or Felicia Cannon on season 25). Dick Donato from *Big Brother 8* is the only houseguest over 40 to win, doing so at the age of 44.

BIPOC status is unique in that it is the only demographic factor that the *Big Brother* casting team has explicitly addressed, namely via their aforementioned “50% BIPOC initiative” in 2020. As such, I wanted to examine how the performance of BIPOC houseguests on the show has shifted over time. **Figure 2** displays the cumulative total of BIPOC houseguests making it to the late-game (including winners) by season number, which reveals several trends in the on-show success of members of this community. Overall, as shown in **Figure 1**, BIPOC houseguests have made the upper middle stage of the game at a noticeably lower rate than their non-BIPOC castmates (44% vs 51%); they also have struggled more making it to the late

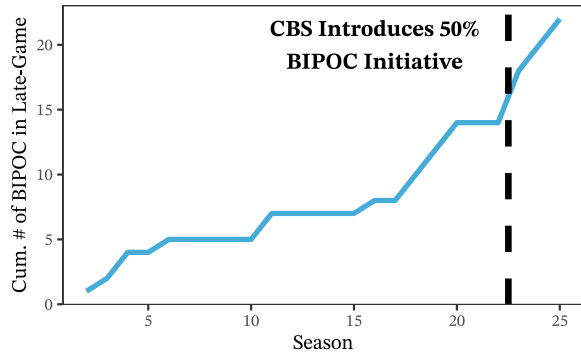


Figure 2: Cumulative total of BIPOC houseguests making it to the late-game stage of *Big Brother* by season number. Late-game stage is defined as placing in the top 25% of contestants on your season, including the winner.

game, although their proportion of winners is on par with that of non-BIPOC (in much thanks to the consecutive wins of 3 BIPOC houseguests in every season since the diversity initiative). Since the diversity initiative, which began after season 22, more BIPOC houseguests have managed to make it to the late-game; this comes after three noticeable stalls where none reached the end (seasons 7-10, 12-15, and 21-22). From exploratory analysis alone, the initiative appears to be increasing equity for BIPOC contestants.

2.2.2 Competition Performance

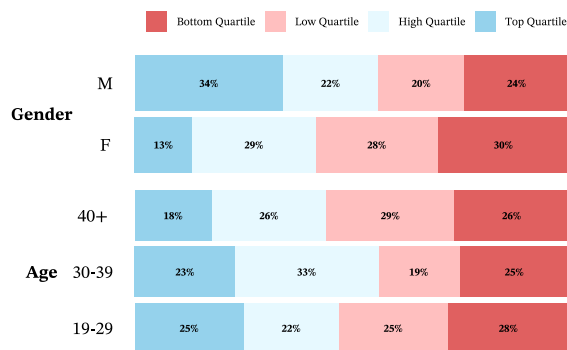


Figure 3: Breakdown of competition performance by demographic group

Figure 3 displays the breakdown of *Big Brother* competition performance by gender and age; these are the only factors examined due to their impact on one’s physicality. There are two main competitions that occur each week of the show: the *Head of Household (HOH)* competition, where the winner gets to nominate two houseguests for possible eviction, and the *Power of Veto (POV)* competi-

tion, where the winner may save one of the two nominees (if they choose to do so, the HOH must then name a replacement nominee). Other competition variants have been introduced over the years, but only HOH and POV wins will count towards a houseguest’s performance.

For *gender*, there is a blatant disparity in competition performance between men and women, signaling that past competitions might be inequitable. The proportion of men in the top quartile of performers on their season is almost triple the proportion for women (34% vs 13%); furthermore, women have been noticeably more often in the bottom half of performers (58% vs 44% for men).

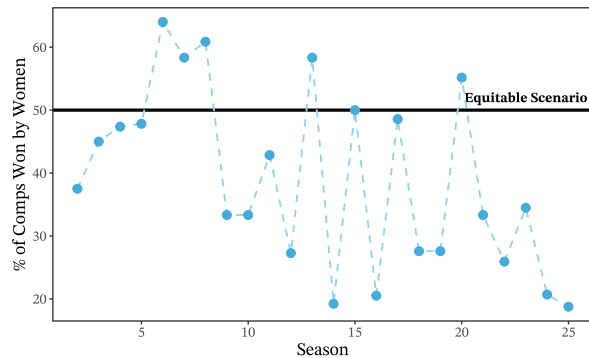


Figure 4: Percent of competitions won by women during each season of *Big Brother*

Figure 4 offers another illustration of the gender imbalance when it comes to competition wins. Women have only won $\geq 50\%$ of competitions in 6 out of 25 seasons; furthermore, more modern seasons of *Big Brother* are seeing historically low win percentages for women. After a new set design was unveiled for season 22, ushering in what some fans have referred to as the “New Era” of the show, women have won $<35\%$ of competitions in every season. Additionally, the most recent iteration, *Big Brother 25*, saw the lowest ever female win percentage at 19%. Viewers have criticized the show for its recent over-reliance on physical competitions, which have historically favored men; older competitions more often involved a social, strategic, or mental aspect, making them more equitable for all contestants.

Disparities in performance are less pronounced for *age*, although there are trends worth mentioning. While 19-29 year old houseguests are split approximately evenly across the board, houseguests over 40 have struggled to make it into the top quartile of competition performers, only doing so 18% of the time. Interestingly, houseguests in their thirties seem to have the upper hand, performing in the top half 56% of the time (compared to 44% for 40+ and 47% for 19-29).

2.3 Model

2.3.1 Placement

Being that I have broken up placement into five ordered categories, I chose to conduct ordinal logistic regression to model placement based on BIPOC status, LGBT status, gender, and age. Since *Big Brother* has fundamentally changed the way they cast seasons based on BIPOC status, I also wanted to include potential effects of the 2020 diversity initiative. To do so, I created a binary indicator for each houseguest which designates whether they competed on the show before or after the initiative (1 = After, 0 = Before). This indicator variable’s interaction with BIPOC status will be included as a predictor in the model.

A *proportional odds model* is the most widely used model for ordinal response variables; it fits a binomial logistic regression model at each consecutive level of the response variable, so we can see what factors are associated with higher response values (McCullagh 1980). The proportional odds model makes four assumptions:

- The response variable is ordinal
- One or more of the explanatory variables are either continuous, categorical, or ordinal
- There is no multicollinearity between the explanatory variables
- Proportional odds, where each explanatory variable has the same effect at each cumulative split of the response

Table 1: Results of Brant-Wald test for proportional odds model on placement

	X-squared	DF	Prob
Omnibus	12.21	18	0.84
BIPOC	2.83	3	0.42
LGBT	1.11	3	0.77
Gender	3.76	3	0.29
Age	4.51	3	0.21
Initiative	0.56	3	0.91
BIPOC:Initiative	1.17	3	0.76

The first two assumptions are met by how the data has been constructed and wrangled. The third assumption was met by verifying that the variance inflation factors (VIFs) for all explanatory variables were under a threshold (see **Appendix**). The fourth assumption can be verified with a Brant-Wald test, where probability values below 0.05 indicate that the coefficient is in violation of proportional odds (McNulty 2021).

Table 1 displays the results of the Brant-Wald test, which

show no violations of proportional odds; therefore, I proceed with this model. The placement model will take on the form:

$$\begin{aligned} \text{logit}(P(Y_i \leq j)) = & \alpha_j + \beta_1 * \text{BIPOC}_i + \beta_2 * \text{LGBT}_i \\ & + \beta_3 * \text{Gender}_i + \beta_4 * \text{Age}_i + \beta_5 * \text{Initiative}_i \\ & + \beta_6 * (\text{Initiative}_i * \text{BIPOC}_i) \end{aligned}$$

where i is the observation, α is the intercept, and j is the level of the response variable.

2.3.2 Competition Performance

Being that I have broken up competition performance into four ordered categories, I also chose to conduct ordinal logistic regression to model competition performance based on age and gender. While the first three assumptions of a proportional odds model are met, the Brant-Wald test (as seen in **Table 2**) indicated that gender was in violation of the proportional odds assumption.

Table 2: Results of Brant-Wald test for proportional odds model on competitive performance

	X-squared	DF	Prob
Omnibus	10.12	4	0.04
Gender	9.88	2	0.01
Age	0.42	2	0.81

To address this violation, competition performance will be studied with a *partial proportional odds model* (Peterson and Harrell Jr 1990), which stipulates that the effect of gender is not the same across all levels of competition performance (although the opposite is true for age). The competition performance model will take on the form:

$$\text{logit}(P(Y_i \leq j)) = \alpha_j + \beta_1 * \text{Age}_i + \beta_{j2} * \text{Gender}_i$$

where i is the observation, α is the intercept, and j is the level of the response variable. The coefficient for gender will take on a different value at each split of competition performance (below Low Quartile, below High Quartile, and below Top Quartile).

3 Results

3.1 Placement

As described, a proportional odds model was fit for placement, using the `polr` function from the MASS library in R.

Table 3: Estimated coefficients from proportional odds model for placement

	Est	SE	OR (90% CI)
BIPOC	-0.41	0.23	0.66 (0.45, 0.96)
LGBT	0.06	0.28	1.07 (0.67, 1.69)
Gender	0.14	0.19	1.16 (0.84, 1.59)
Age	0.01	0.01	1.01 (0.99, 1.03)
Initiative	-0.54	0.38	0.58 (0.31, 1.09)
BIPOC:Initiative	1.29	0.56	3.62 (1.43, 9.2)

Table 4: Estimated intercepts from proportional odds model for placement

	Est	SE
> Early Out	-0.84	0.40
> Lower Middle	0.20	0.40
> Upper Middle	1.35	0.41
> Late Game	2.83	0.45

Table 3 and **Table 4** display the output from the placement model. The model shows that BIPOC status (at the $\alpha = 0.1$ level) and the interaction between BIPOC status and post-diversity-initiative status (at the $\alpha = 0.05$ level) are significantly associated with placement bucket. The coefficient estimates for gender, LGBT status, and age are not significant, indicating that there is not enough evidence that these demographic factors are associated with placement bucket.

Being that the model contains an interaction term, the interpretation of the main effect of BIPOC status is altered. Using **Table 3**, the model finds that a BIPOC contestant has approximately 34% lower odds (OR = 0.66) of achieving a better placement bucket in *Big Brother* versus a non-BIPOC contestant, holding all other variables constant *and* assuming the interaction variable is in its reference case value (meaning the contestant is playing before the diversity initiative).

A more sophisticated interpretation of the interaction effect can be achieved by examining the predicted probabilities for each placement bucket in each combination of BIPOC status and post-diversity-initiative status. This can be implemented with the `allEffects` function from the `effects` library in R (Fox et al. 2016).

Table 5 shows that, holding all other variables constant, the predicted probability of winning for BIPOC contestants has doubled since the diversity initiative; additionally, the predicted probability of being an early out has been almost cut in half.

Table 5: Predicted probabilities for each placement bucket by BIPOC status and post-diversity-initiative status. Column names are in the format *BIPOC_Initiative*. For BIPOC, 1 = Yes and 0 = No. For Initiative, 1 = After and 0 = Before.

Placement	0_0	0_1	1_0	1_1
P(Early Out)	0.25	0.36	0.33	0.19
P(Lower Middle)	0.23	0.25	0.25	0.21
P(Upper Middle)	0.26	0.22	0.23	0.28
P(Late Game)	0.18	0.12	0.14	0.23
P(Winner)	0.07	0.04	0.05	0.10

3.2 Competition Performance

As described, a partial proportional odds model was fit for competition performance, using the `vg1m` function from the `VGAM` library in R.

Table 6: Estimated coefficients from partial proportional odds model for competition performance

	Est	SE	OR (90% CI)
Age	0.01	0.01	1.01 (0.99, 1.03)
Gender, < Low	-0.32	0.24	0.73 (0.49, 1.08)
Gender, < High	-0.59	0.22	0.55 (0.39, 0.79)
Gender, < Top	-1.24	0.27	0.29 (0.18, 0.45)

Table 7: Estimated intercepts from partial proportional odds model for competition performance

	Estimate	Std. Error
< Low Quartile	-1.13	0.41
< High Quartile	0.04	0.40
< Top Quartile	1.60	0.43

Table 6 and **Table 7** display the output from the competition performance model. The model shows that gender is significantly associated with competition performance below “High Quartile” (at the $\alpha = 0.01$ level) and below “Top Quartile” (at the $\alpha = 0.001$ level). The coefficient estimate for age is not significant, indicating there is not enough evidence that it is associated with competition performance quartile; interestingly, the coefficient estimate for gender is also not significant below “Low Quartile”, meaning gender is not a significant predictor on whether or not a contestant is in the worst 25% of competition performers on their season.

The main effects for a partial proportional odds model must be interpreted differently than those from a full

proportional odds model. Using **Table 6**, the model finds that a male contestant has approximately 45% lower odds (OR = 0.55) of being at or below the “Low Quartile” (bottom 50%) of competition performers on their season versus a female contestant; additionally, a male contestant has approximately 71% lower odds (OR = 0.29) of being at or below the “High Quartile” (bottom 75%) versus a female contestant (holding all other variables constant for each interpretation).

The goodness-of-fit for both the placement model and the competition performance model was assessed with the Hosmer-Lemeshow, Lipsitz, and Pulksteins-Robinson tests, which are all recommended model diagnostics for ordinal regression (Fagerland and Hosmer 2017). These tests were implemented with the `gofcat` library in R (Ugba 2022); no test showed significant evidence of a lack of fit for either model (see **Appendix**).

4 Discussion

This project examined data from all 357 houseguests on the last 24 US seasons of *Big Brother* in an attempt to gauge whether the game is equitable for contestants of different demographic backgrounds. The analysis dived into historical disparities in performance on the show and communicated clear trends that illustrated how *Big Brother* could improve (or has improved) fairness.

First, BIPOC houseguests have historically struggled to make it further in the game compared to their non-BIPOC castmates, but the 2020 CBS diversity initiative is helping to bridge this gap (and then some). Results from the exploratory data analysis and the proportional odds model on placement showed that BIPOC contestants had a noticeably lower rate of placing in the top half of houseguests on their season (44% vs 51%); additionally, holding all other variables constant, their odds of making it to a further stage in the game were 34% lower than that of non-BIPOC before *Big Brother 22*. Starting with *Big Brother 23*, however, CBS’s requirement of 50% BIPOC casts has turned the tides for performance of racial and ethnic minorities on the show. In every season since the initiative, BIPOC houseguests have comprised at least half of the contestants remaining in the late-game, and the amount of BIPOC winners has doubled. Furthermore, holding all other variables constant, BIPOC houseguests are predicted to win at twice the rate, and to place in the lower half at half the rate.

It is important to note the limitations of the proposed approach for analyzing placement. First, the decision to combine BIPOC houseguests into one category may overgeneralize the experiences of racial/ethnic minorities on *Big Brother*; particularly, the experiences of Black

contestants on the show have been historically more difficult, a nuance that cannot be entirely captured by this analysis. The BIPOC binary indicator is not meant to treat non-White contestants as a monolith, but rather it is used to examine the effects of CBS’s diversity initiative (which uses this term). On a related note, only three seasons have occurred since the initiative, meaning its effects could potentially be overstated due to the low sample size. For example, on *Big Brother 23*, an alliance between the six Black houseguests formed to ensure the show would finally crown its first Black winner; these houseguests all made the final 6, which likely made a large influence on the predicted probabilities of placement for BIPOC houseguests after the initiative. Revisiting this analysis after more seasons have occurred could help validate the effectiveness of the increased diversity in casting. Finally, with the cumulative nature of a proportional odds model, we cannot entirely analyze the relationship between demographic factors and being in specific placement buckets. For example, the exploratory data analysis showed a large disparity in the proportion of men winning versus women winning, but the coefficient for gender in the placement model was not significant. Potential barriers between making the late game and winning, for example, could be better studied with an *adjacent category model* (Fullerton and Xu 2018).

Second, *Big Brother* competitions have historically favored men, with women having much lower odds of emerging as top performers. The exploratory data analysis found that men have ranked in the top 25% in competition wins on their season at almost triple the rate of women, and the problem does not seem to be letting up as recent seasons have displayed historically high gender imbalances in terms of overall win percentage. Compared to a female contestant (and holding age constant), results from the partial proportional odds model found that a male contestant has much lower odds of performing in the bottom half or the bottom quartile on their season.

The proposed approach for analyzing competition performance also has noteworthy limitations. First, while the analysis only involves age and gender due to their impacts on one’s physicality, there may be other factors with a potential impact. Further exploratory analysis (see **Appendix**) found that BIPOC contestants have historically performed worse in competitions, falling into the bottom quartile on their season 36% of the time (compared to 24% for non-BIPOC contestants). Unlike age and gender, there is not an immediately reasonable explanation for this disparity; future analysis should examine this potential inequity and if it has been helped by the diversity initiative. Second, it is important to note the confounding variables that come with a houseguest being on one season versus another—for example, different sea-

sons having more strategically and physically competent players. A mixed-effect model was considered to mitigate this, but it would have created estimability issues being that there is not replicated data within each season (for example, there is only one winner per season). Instead, I aim to address this problem by normalizing variables to reduce the effect of season-specific characteristics, although between-season variability remains a prevalent issue in analysis of reality TV competitions.

Overall, this analysis suggests that inequity has been a problem over *Big Brother*'s lifetime, particularly for BIPOC (in terms of placement) and women (in terms of competitions). Show producers could address these issues by maintaining consistent diversity in casting (as the BIPOC initiative has already shown promising effects) and leveling the playing field by including more mental and/or social-strategic challenges.

Appendix

4.1 Exploratory Data Analysis

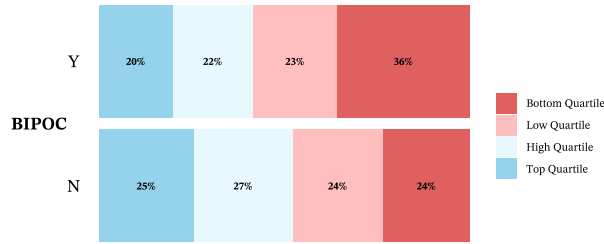


Figure 5: Breakdown of competition performance by BIPOC status

4.2 Model Assumptions

Table 8: Variance inflation factors for placement model. A VIF > 5 indicates multicollinearity may be present.

	VIF
BIPOC	1.27
LGBT	1.03
Gender	1.04
Age	1.03
Initiative	1.96
BIPOC:Initiative	2.30

Table 9: Variance inflation factors for competition performance model. A VIF > 5 indicates multicollinearity may be present.

	VIF
Gender	1.01
Age	1.01

4.3 Model Diagnostics

Table 10: Results of Lipsitz test for placement model. H_0 is that no lack of fit is detected.

LRT	df	p
6.51	9	0.69

Table 11: Results of Pulksteins-Robinson test for placement model. H_0 is that no lack of fit is detected.

X-squared	df	p
117.1	119	0.53

Table 12: Results of Hosmerlem-Lemeshow test for placement model. H_0 is that no lack of fit is detected.

X-squared	df	p
35.05	35	0.47

Table 13: Results of Lipsitz test for competition performance model. H_0 is that no lack of fit is detected.

LRT	df	p
12.81	9	0.17

Table 14: Results of Pulksteins-Robinson test for competition performance model. H_0 is that no lack of fit is detected.

X-squared	df	p
8.11	7	0.32

Table 15: Results of Hosmerlem-Lemeshow test for competition performance model. H_0 is that no lack of fit is detected.

X-squared	df	p
31.33	26	0.22

References

- Chan, Anna. 2013. “‘Big Brother’ Airs Contestants’ Racist, Homophobic Remarks.” *TODAY*. NBC Universal. <https://www.today.com/popculture/big-brother-air-contestants-racist-homophobic-remarks-6c10560772>.
- Dixon, Vince. 2019. “Methodology Behind Big Brother Diversity Data Dive.” *Vince Dixon Portfolio*. Vince Dixon. <https://vinedixonportfolio.com/2019/08/29/methodology-behind-big-brother-diversity-data-dive/>.
- Fagerland, Morten W, and David W Hosmer. 2017. “How to Test for Goodness of Fit in Ordinal Logistic Regression Models.” *The Stata Journal* 17 (3): 668–86.
- Fox, John, Sanford Weisberg, Michael Friendly, Jangman Hong, Robert Andersen, David Firth, Steve Taylor, and Maintainer John Fox. 2016. “Package ‘Effects’.” *Url: Http://Www. R-Project. Org, Http://Socserv. Socsci. Mcmaster. Ca/Jfox*.
- Fullerton, Andrew S, and Jun Xu. 2018. “Constrained and Unconstrained Partial Adjacent Category Logit Models for Ordinal Response Variables.” *Sociological Methods & Research* 47 (2): 169–206.
- Hines, Ree. 2013. “‘Big Brother’ Contestants Lose Jobs Due to Racist, Homophobic Remarks.” *TODAY*. NBC Universal. <https://www.today.com/popculture/big-brother-contestants-lose-jobs-due-racist-homophobic-remarks-4b11210469>.
- McCullagh, Peter. 1980. “Regression Models for Ordinal Data.” *Journal of the Royal Statistical Society: Series B (Methodological)* 42 (2): 109–27.
- McNulty, Keith. 2021. *Handbook of Regression Modeling in People Analytics: With Examples in r and Python*. CRC Press.
- Peterson, Bercedis, and Frank E Harrell Jr. 1990. “Partial Proportional Odds Models for Ordinal Response Variables.” *Journal of the Royal Statistical Society: Series C (Applied Statistics)* 39 (2): 205–17.
- Siwak, Miranda. 2023. “‘BB25’ Fans Think ‘Pressure Cooker’ Didn’t Accommodate Deaflympian Matt.” *AOL*. Yahoo. <https://www.aol.com/bb25-fans-think-pressure-cooker-154620589.html>.
- “The Big Brother Wiki.” n.d. *Big Brother Wiki*. Fandom TV. https://bigbrother.fandom.com/wiki/Big_Brother_Wiki.
- Ugba, Ejike R. 2022. “Gofcat: An r Package for Goodness-of-Fit of Categorical Response Models.” *Journal of Open Source Software* 7 (76): 4382.
- Whitten, Sarah. 2020. “CBS Reality Shows Must Now Have 50.” *CNBC*. CNBC LLC. <https://www.cNBC.com/2020/11/09/cbs-reality-shows-must-now-have-50percent-non-white-casts-network-says.html>.