Assessing Referee Impartiality: The Likelihood of Red Cards for Dark-Skin-Toned Players in Soccer

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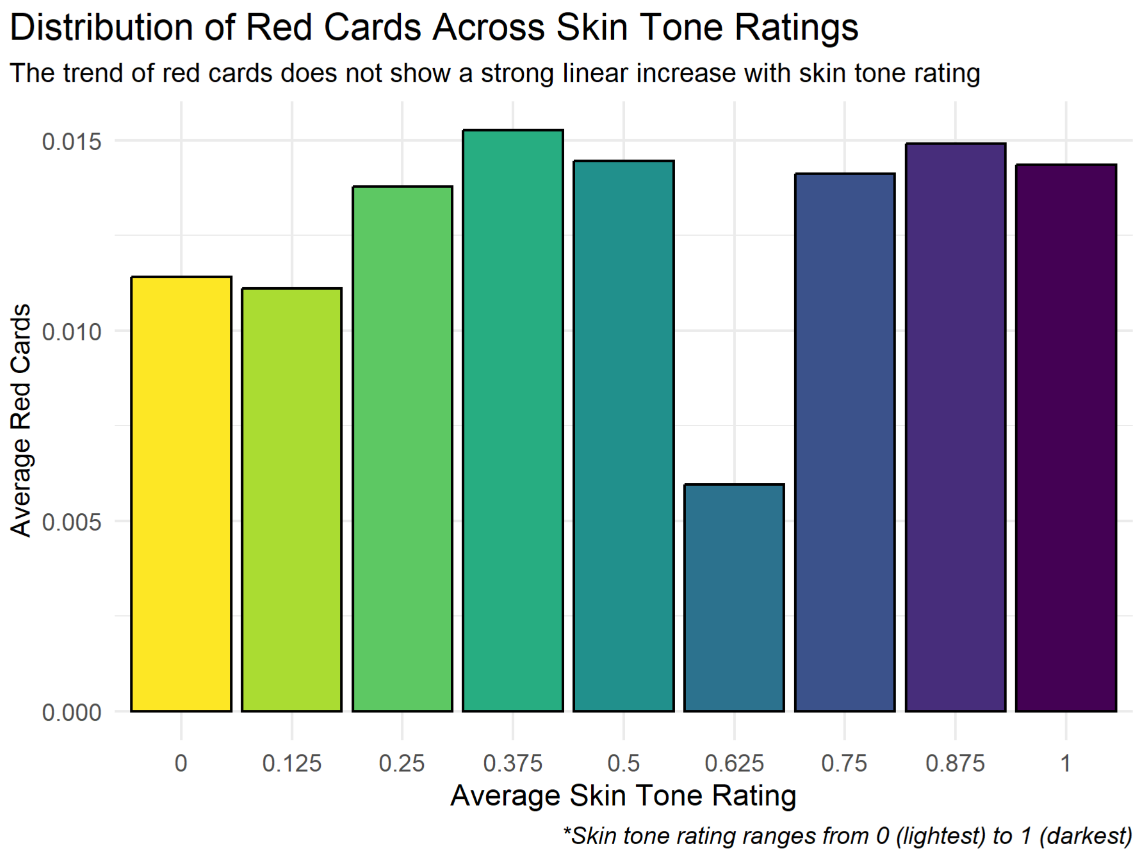
Dataset

- playerShort: The short name of the player, useful for identification.
- club: The club for which the player plays, indicating the team context of the player's performance.
- leagueCountry: The country of the league in which the player competes, which could relate to different refereeing styles and biases.
- position: The position the player plays, relevant since certain positions might receive more red cards.
- games: The number of games played, essential for calculating rates like red cards per game. = yellowCards: The number of yellow cards received, which could indicate a player's disciplinary record.
- redCards: The number of red cards received, a key variable for your analysis.
- rater1 and rater2: Skin tone rating by two different raters, which is central to analyzing potential bias.
- meanIAT: The mean Implicit Association Test score for the referee country, measuring implicit bias levels.

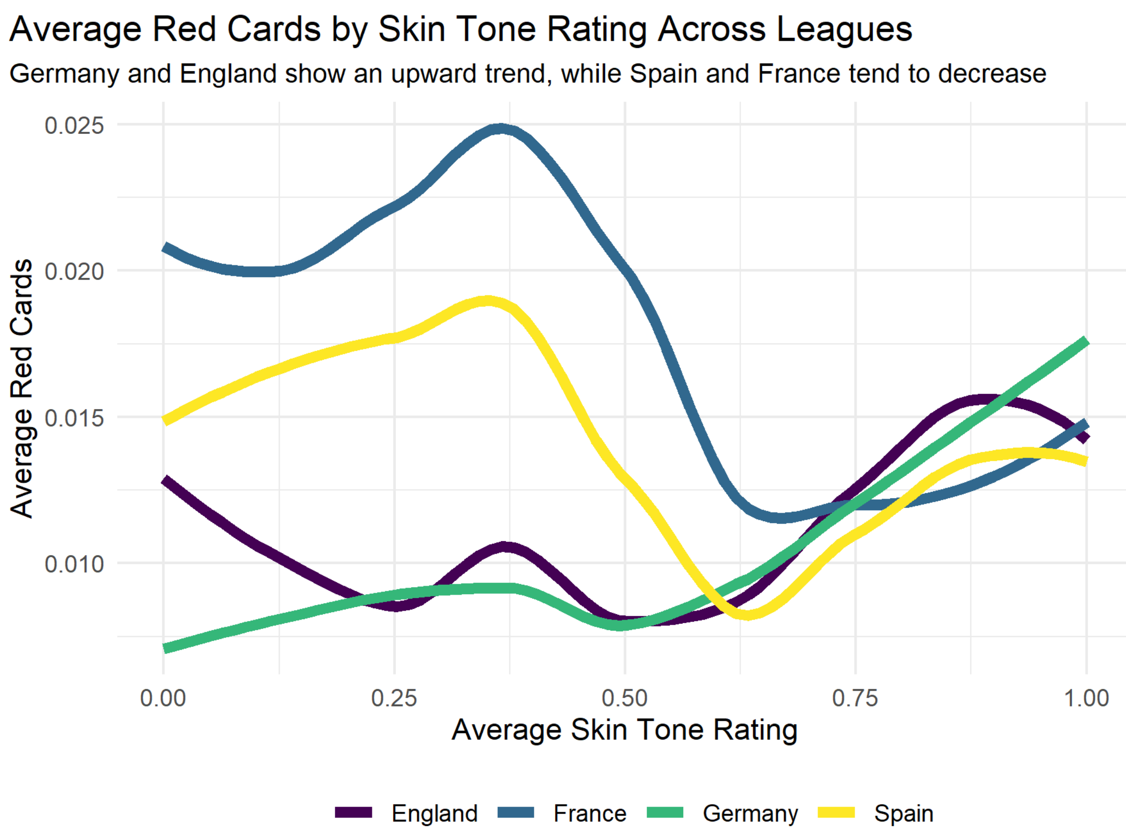
First approach

```
data <- read.csv("CrowdstormingDataJuly1st.csv")
data$mean_rating <- rowMeans(data[,c("rater1", "rater2")], na.rm = TRUE)
clean_data <-  na.omit(data)

avg_red_cards <- clean_data %>%
```

```
  group_by(mean_rating) %>%
  summarise(average_reds = mean(redCards))

ggplot(avg_red_cards, aes(x = as.factor(mean_rating), y = average_reds, fill = as.factor(mean
  geom_bar(stat = "identity", color = "black") +
  scale_fill_viridis(discrete = TRUE, direction = -1) +
  theme_minimal() +
  theme(legend.position = "none",
        axis.title.y = element_text(size = 10),
        plot.caption = element_text(face = "italic"),
        plot.title = element_text(hjust = 0, size = 14),
        plot.subtitle = element_text(hjust = 0, size = 10),
        plot.title.position = "plot") +
  labs(title = "Distribution of Red Cards Across Skin Tone Ratings",
       subtitle = "The trend of red cards does not show a strong linear increase with skin to
       caption = "*Skin tone rating ranges from 0 (lightest) to 1 (darkest)",
       x = "Average Skin Tone Rating", y = "Average Red Cards")
```

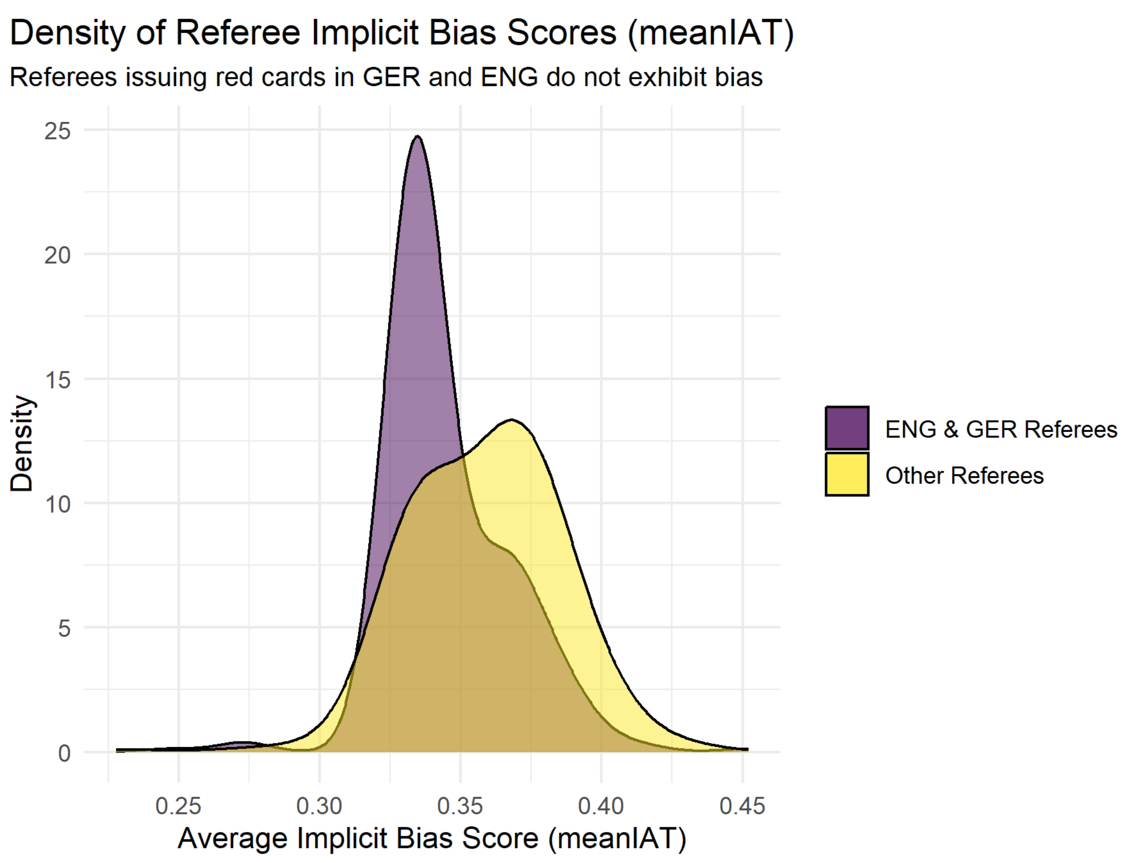


```r
avg_red_cards_league <- clean_data %>%
  group_by(leagueCountry, mean_rating) %>%
  summarise(average_reds = mean(redCards))

ggplot(avg_red_cards_league, aes(x = mean_rating, y = average_reds, group = leagueCountry, co
  geom_smooth(se = FALSE, size = 2) +
  scale_color_viridis(discrete = TRUE, option = "D") +
  theme_minimal() +
  labs(x = "Average Skin Tone Rating",
       y = "Average Red Cards",
       title = "Average Red Cards by Skin Tone Rating Across Leagues",
       subtitle = "Germany and England show an upward trend, while Spain and France tend to d
  theme(legend.title = element_blank(),
        legend.position = "bottom",
        plot.title = element_text(hjust = 0),
        plot.subtitle = element_text(hjust = 0, size = 10),
        plot.caption = element_text(hjust = 0.5),
        plot.title.position = "plot")
```




```
eng_ger_ref_data <- clean_data %>%
  filter(leagueCountry %in% c("England", "Germany"), redCards > 0) %>%
  group_by(refNum) %>%
  summarise(avg_meanIAT = mean(meanIAT, na.rm = TRUE)) %>%
  ungroup()

avg_meanIAT_eng_ger <- mean(eng_ger_ref_data$avg_meanIAT)

other_ref_data <- clean_data %>%
  filter(!leagueCountry %in% c("England", "Germany"), redCards > 0) %>%
  group_by(refNum) %>%
  summarise(avg_meanIAT = mean(meanIAT, na.rm = TRUE)) %>%
  ungroup()

avg_meanIAT_other <- mean(other_ref_data$avg_meanIAT)

avg_data <- data.frame(
```

```
  League = c("England & Germany", "Other Leagues"),
  avg_meanIAT = c(avg_meanIAT_eng_ger, avg_meanIAT_other)
)

ggplot() +
  geom_density(data = eng_ger_ref_data, aes(x = avg_meanIAT, fill = "ENG & GER Referees"), al
  geom_density(data = other_ref_data, aes(x = avg_meanIAT, fill = "Other Referees"), alpha =
  scale_fill_viridis(discrete = TRUE) +
  labs(title = "Density of Referee Implicit Bias Scores (meanIAT)",
       subtitle = "Referees issuing red cards in GER and ENG do not exhibit bias",
       x = "Average Implicit Bias Score (meanIAT)",
       y = "Density") +
  theme_minimal() +
  theme(legend.title = element_blank(),
        plot.subtitle = element_text(size = 10, hjust = 0),
        plot.title.position = "plot")
```



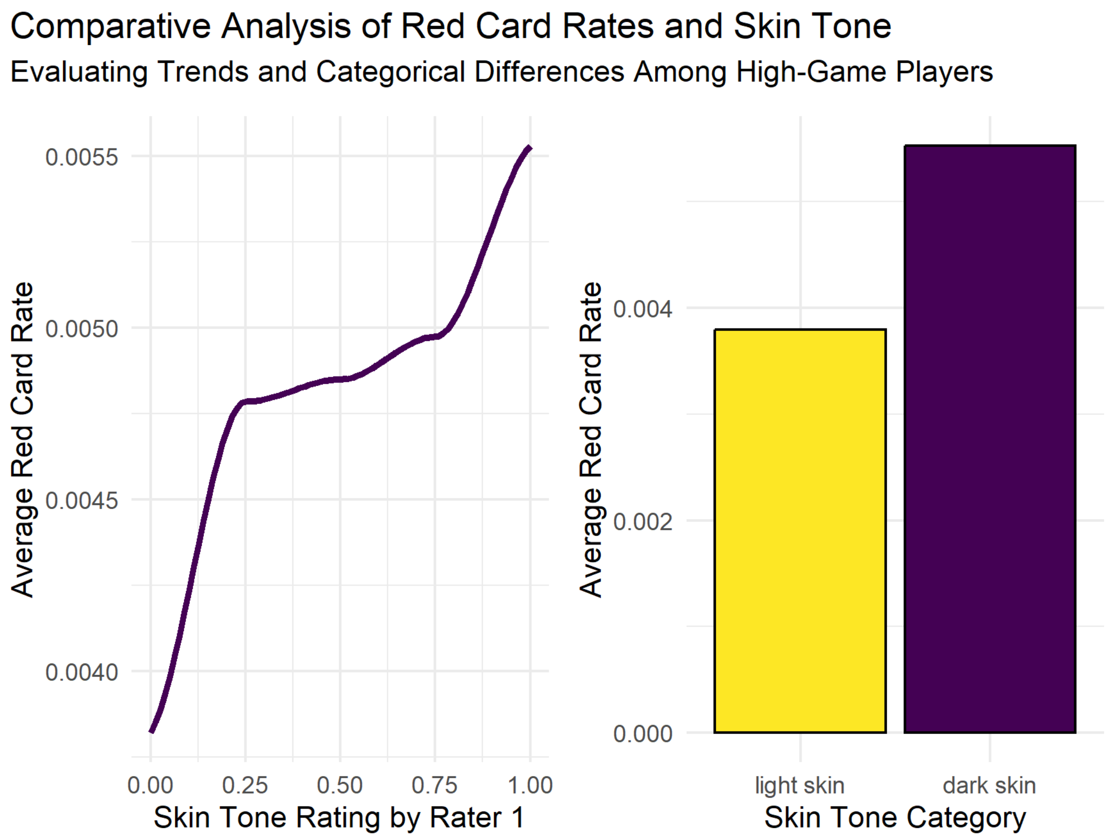
- First Visual (Bar Plot: Distribution of Red Cards Across Skin Tone Ratings) This bar plot displays the average number of red cards given to players across different average skin tone ratings, ranging from 0 (lightest) to 1 (darkest).
- Second Visual (Line Plot: Average Red Cards by Skin Tone Rating Across Leagues) This line plot compares the trends in average red cards given within different European football leagues relative to players' average skin tone ratings.
- Third Visual (Density Plot: Density of Referee Implicit Bias Scores (meanIAT)) This density plot compares the implicit bias scores (meanIAT) of referees who gave red cards in German and English leagues against other referees.

Second approach

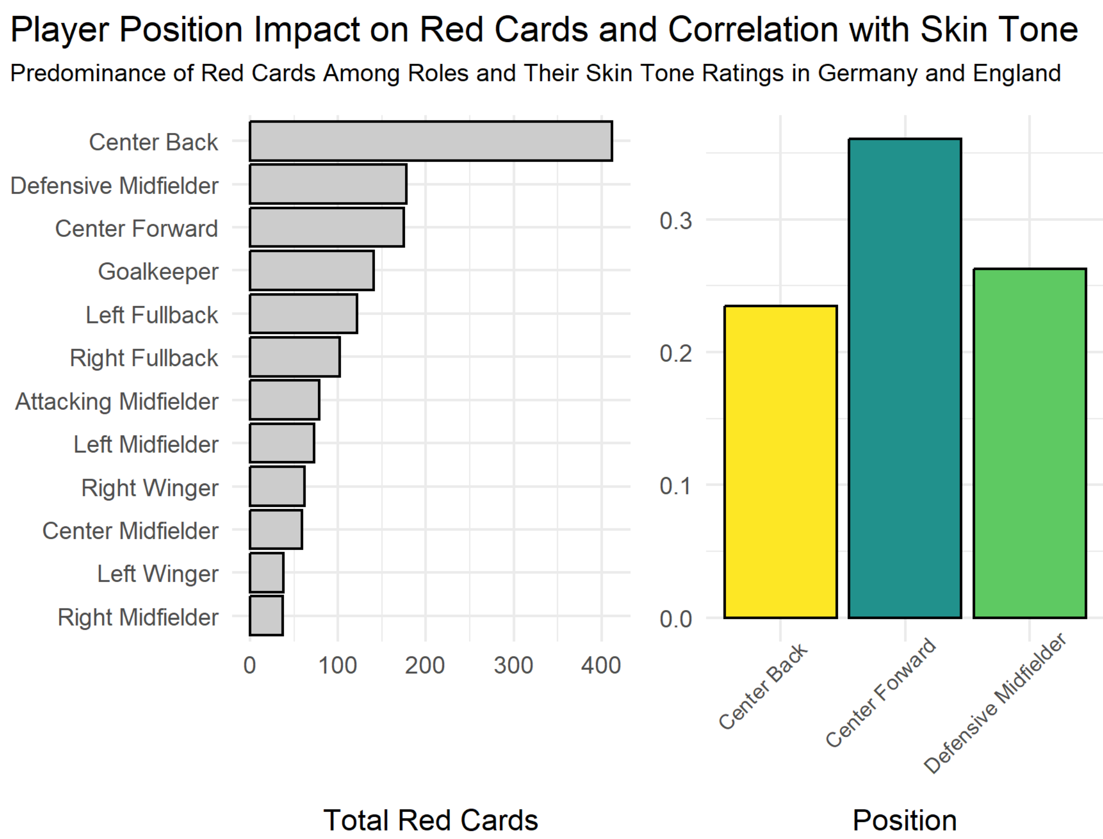
```
median_games <- median(clean_data$games)
high_game_players <- clean_data %>%
  filter(games > median_games)

high_game_players <- high_game_players %>%
  mutate(red_card_rate = redCards / games)

avg_red_card_rate <- high_game_players %>%
  group_by(rater1) %>%
  summarise(average_red_card_rate = mean(red_card_rate))

plot1 <- ggplot(avg_red_card_rate, aes(x = rater1, y = average_red_card_rate, group = 1)) +
  geom_smooth(method = "loess", se = FALSE, color = "#440154", size = 1.2) +
  theme_minimal() +
  theme(plot.title.position = "plot") +
  labs(x = "Skin Tone Rating by Rater 1",
       y = "Average Red Card Rate")


high_game_players$skin_tone_category <- ifelse(high_game_players$mean_rating <= 0.2, "light s
                                               ifelse(high_game_players$mean_rating >= 0.8, "

high_game_players <- na.omit(high_game_players)

avg_red_card_rate_by_skin_tone <- high_game_players %>%
  group_by(skin_tone_category) %>%
  summarise(average_red_card_rate = mean(red_card_rate, na.rm = TRUE))
```

```
avg_red_card_rate_by_skin_tone$skin_tone_category <- factor(avg_red_card_rate_by_skin_tone$sk
                                                            levels = c("light skin", "dark sk


plot2 <- ggplot(avg_red_card_rate_by_skin_tone, aes(x = skin_tone_category, y = average_red_c
  geom_bar(stat = "identity", color = "black") +
  scale_fill_viridis(discrete = TRUE, direction = -1) +
  theme_minimal() +
  labs(x = "Skin Tone Category",
       y = "Average Red Card Rate") +
  theme(legend.position = "none",
        plot.title.position = "plot",
        plot.subtitle = element_text(size = 10))

position_red_cards <- clean_data %>%
  group_by(position) %>%
  summarise(total_red_cards = sum(redCards)) %>%
  ungroup()

position_red_cards <- position_red_cards %>%
  arrange(desc(total_red_cards))

plot3 <- ggplot(position_red_cards, aes(x = reorder(position, total_red_cards), y = total_red
  geom_bar(stat = "identity", color = "black", fill = "grey80") +
  coord_flip() +
  theme_minimal() +
  labs(x = "Position", y = "Total Red Cards") +
  theme(plot.title.position = "plot",
        axis.title.y = element_blank(),
        plot.subtitle = element_text(size = 10))

filtered_data <- clean_data %>%
  filter(leagueCountry %in% c("Germany", "England"),
         position %in% c("Center Back", "Defensive Midfielder", "Center Forward"))

position_skin_tones <- filtered_data %>%
  group_by(position) %>%
  summarise(average_skin_tone = mean(mean_rating, na.rm = TRUE),
            skin_tone_sd = sd(mean_rating, na.rm = TRUE)) %>%
  ungroup()
```

```r
plot4 <- ggplot(position_skin_tones, aes(x = position, y = average_skin_tone, fill = factor(p
  geom_bar(stat = "identity", color = "black") +
  scale_fill_manual(values = c("Center Back" = "#fde725", "Defensive Midfielder" = "#5ec962"
  theme_minimal() +
  labs(x = "Position", y = "Average Skin Tone Rating") +
  theme(legend.position = "none",
        legend.text = element_text(size = 8),
        plot.title.position = "plot",
        axis.title.y = element_blank(),
        axis.text.x = element_text(angle = 45,vjust = 1, hjust = 0.8, size = 8),
        plot.subtitle = element_text(size = 10))

combined_plot1 <- plot1 + plot2
combined_plot1 + plot_annotation(
  title = "Comparative Analysis of Red Card Rates and Skin Tone",
  subtitle = "Evaluating Trends and Categorical Differences Among High-Game Players"
)
```



```
combined_plot2 <- plot3 + plot4
combined_plot2 + plot_annotation(
  title = "Player Position Impact on Red Cards and Correlation with Skin Tone",
  subtitle = "Predominance of Red Cards Among Roles and Their Skin Tone Ratings in Germany ar
) &
  theme(
    plot.subtitle = element_text(size = 9))
```



- First Visual (Line and Bar Plot: Red Card Rate vs. Skin Tone Rating)

This visual combines a line graph showing the average red card rate across different skin tone ratings and a bar chart comparing the average red card rate between light and dark skin categories among players with high game appearances.

- Second Visual (Bar Plot: Total Red Cards by Position & Skin Tone in Specific Leagues)

This visual showcases a bar chart detailing the total red cards received by player position, paired with a bar chart showing the average skin tone for positions with the most red cards in the German and English leagues.

Reference

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Many Analysts, One Data Set: Making Transparent How Variations in Analytic Choices Affect Results

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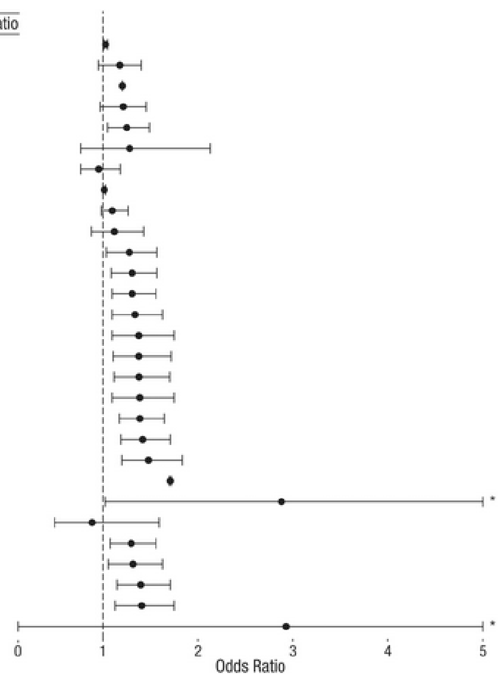
Abstract

Twenty-nine teams involving 61 analysts used the same data set to address the same research question: whether soccer referees are more likely to give red cards to dark-skin-toned players than to light-skin-toned players. Analytic approaches varied widely across the teams, and the estimated effect sizes ranged from 0.89 to 2.93 (*Mdn* = 1.31) in odds-ratio units. Twenty teams (69%) found a statistically significant positive effect, and 9 teams (31%) did not observe a significant relationship. Overall, the 29 different analyses used 21 unique combinations of covariates. Neither analysts' prior beliefs about the effect of interest nor their level of expertise readily explained the variation in the outcomes of the analyses. Peer ratings of the quality of the analyses also did not account for the variability. These findings suggest that significant variation in the results of analyses of complex data may be difficult to avoid, even by experts with honest intentions. Crowdsourcing data analysis, a strategy in which numerous research teams are recruited to simultaneously investigate the same research question, makes transparent how defensible, yet subjective, analytic choices influence research results.

Team	Analytic Approach	Distribution	Odds Ratio
10	Multilevel Regression and Logistic Regression	Linear	1.03
1	OLS Regression With Robust Standard Errors, Logistic Regression	Linear	1.18
4	Spearman Correlation	Linear	1.21
14	WLS Regression With Clustered Standard Errors	Linear	1.21
11	Multiple Linear Regression	Linear	1.25
6	Linear Probability Model	Linear	1.28
17	Bayesian Logistic Regression	Logistic	0.96
15	Hierarchical Log-Linear Modeling	Logistic	1.02
18	Hierarchical Bayes Model	Logistic	1.10
31	Logistic Regression	Logistic	1.12
30	Clustered Robust Binomial Logistic Regression	Logistic	1.28
3	Multilevel Logistic Regression Using Bayesian Inference	Logistic	1.31
23	Mixed-Model Logistic Regression	Logistic	1.31
2	Linear Probability Model, Logistic Regression	Logistic	1.34
5	Generalized Linear Mixed Models	Logistic	1.38
24	Multilevel Logistic Regression	Logistic	1.38
28	Mixed-Effects Logistic Regression	Logistic	1.38
32	Generalized Linear Models for Binary Data	Logistic	1.39
8	Negative Binomial Regression With a Log Link	Logistic	1.39
25	Multilevel Logistic Binomial Regression	Logistic	1.42
9	Generalized Linear Mixed-Effects Models With a Logit Link	Logistic	1.48
7	Dirichlet-Process Bayesian Clustering	Misc	1.71
21	Tobit Regression	Misc	2.88
12	Zero-Inflated Poisson Regression	Poisson	0.89
26	Hierarchical Generalized Linear Modeling With Poisson Sampling	Poisson	1.30
16	Hierarchical Poisson Regression	Poisson	1.32
20	Cross-Classified Multilevel Negative Binomial Model	Poisson	1.40
13	Poisson Multilevel Modeling	Poisson	1.41
27	Poisson Regression	Poisson	2.93



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