Aggression on Ice

An analysis of the impact of NHL players' hits/ aggressiveness and how it contributes to success

By: Annabel Steiner, Akshay Gududuru, Corey Udell, Indira Van Kanegan, Jacob Myers, Tabitha Michalski

Introduction

Hockey is a dynamic and strategically demanding sport known for its fast pace of play and emphasis on physicality. Within the game, one impactful aspect is checking, where players utilize body contact to gain possession of the puck, disrupt opponents, and assert their strength and dominance over fellow players. Understanding the patterns and effectiveness of aggression in hockey is essential not only for coaches and players seeking to refine their game plan and strategy but also for researchers aiming to delve deeper into the intricacies of the game and uncover new insights that can enhance our understanding of player behavior and team dynamics.

In our study, we aim to address two key research questions. Our first question examines how the spread of player aggression affects the outcome of the match. We aimed to determine if it was more beneficial and/or impactful to have involvement in aggressive actions spread over a multitude of players or concentrated among a select few. This analysis could then offer NHL coaches insights into optimizing the distribution of aggression across players during a match to improve their chances of winning.

Our second question investigates whether the relative aggression of each team can be used to predict the outcome of a match. Our goal was to determine if the proportion of hits, open ice hits, and penalties dealt by a team could be utilized to create a model that accurately predicts if that team won the match. This conclusion could then provide NHL coaches with insight to suggest the level of aggression they should employ in their game tactics to increase their chances of winning. By investigating these questions, we seek to contribute to the broader conversation surrounding hockey analytics and provide valuable insights for both teams and researchers alike.

Date	Game ID	Home Team	Away Team	Checking Team
2/8/24	1	Carolina Hurricanes	Colorado Avalanche	Colorado Avalanche
2/8/24	1	Carolina Hurricanes	Colorado Avalanche	Colorado Avalanche
2/8/24	1	Carolina Hurricanes	Colorado Avalanche	Colorado Avalanche
2/8/24	1	Carolina Hurricanes	Colorado Avalanche	Carolina Hurricanes
2/8/24	1	Carolina Hurricanes	Colorado Avalanche	Colorado Avalanche

Player # who was Hit	Player # who Hit	Period	Time	Location
8	62	1	19:21	3
48	42	1	18:52	4
71	20	1	18:46	1
25	7	1	18:26	1
88	3	1	18:08	4

Open Ice? (Y/N)	Penalty? (Y/N)	Power Play	Winner
Y	N	N	Carolina Hurricanes
N	N	N	Carolina Hurricanes
N	N	N	Carolina Hurricanes
N	N	N	Carolina Hurricanes
Y	N	N	Carolina Hurricanes

Table 1: The table above shows the first five observations of our collected data with 14 variables recorded for each observation.

We gathered our data from the one-week span of NHL (National Hockey League) games played between February 7th, 2024, and February 14th, 2024. During that week, 48 games total were played, so we numbered the games in order of when they started and used a random number generator to assign two games to each person in our group. At our own leisure, we each watched recordings of our first assigned game. We decided that if we didn't quite get 50 observations from watching our first game, then we would have to then watch our second game as well. This led to one member watching both of their assigned games while the other five members only had to watch their first. This resulted in a total of seven games being watched.

We have 361 total observations where each observation is one 'check/hit'. Given that small bumps were common between players, we determined as a group that a 'hit' was defined as "an attack that was clearly meant to be aggressive". For each observation, we recorded the date the game was played, the home team, the away team, the team that committed the check, the number of the player who was hit by the check, the number of the player who committed the check, the period and time that the check was committed, the score of the home team, the score of the away team, and the team that won the game in the end. We also recorded three “Yes or No” binary variables. The first being whether or not the check was committed on open ice (not against a wall). The second being if there was a penalty assessed for that check specifically. And last, if the check was committed during a power play. The variable was entered as ‘No’ if it wasn’t, and as the name of the team on the power play if it was. And finally, the last variable we recorded was called “Location”. Based on the image provided in Figure 1, we recorded which of our six declared sections of the rink the check occurred in.

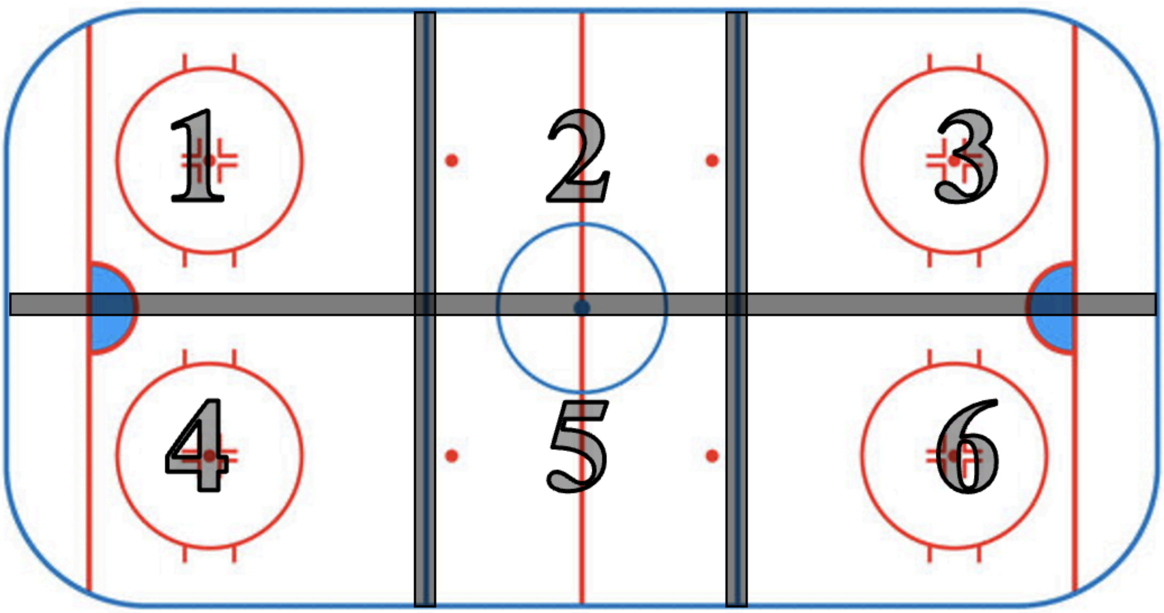


Figure 1: Regulation ice-hockey rink split into 6 sections, oriented with benches on the far side.

Summary

Table 2:

	Yes	No	Yes (Reletive Frequency)	No (Reletive Frequency)
Open Ice Hits	43	318	11.91%	88.09%
Hits Resulting in Penalty	19	342	5.26%	94.74%
Hits During Power Play	47	314	13.02%	86.98%

	Location 1	Location 2	Location 3	Location 4	Location 5	Location 6
Location (Reletive Frequencies)	19.39%	7.78%	19.67%	23.55%	8.58%	21.05%

	Minimum	Maximum	Median	Mean	Standard Deviation
Hits per Game	40	59	52	51.57	15.38
Hits per Period (across all 3 periods)	9	24	18	17.19	2.56
Hits per Player	1	9	2	2.33	1.63
Hits Called as Penalties per Game	1	6	3	2.71	1.75
Hits During Power Play per Game	3	10	7	6.71	2.19

Table 2 summarizes data and offers statistical insights into different aspects of ice hockey gameplay. The top table summarizes our binary variables, displaying the counts and relative frequencies. The middle table displays the relative frequencies of hits in each section. Lastly, the final table summarizes the minimum, maximum, median, mean, and standard deviation of hits on different levels of the game, which offers powerful insights in the frequencies of different game states.

Figure 2:

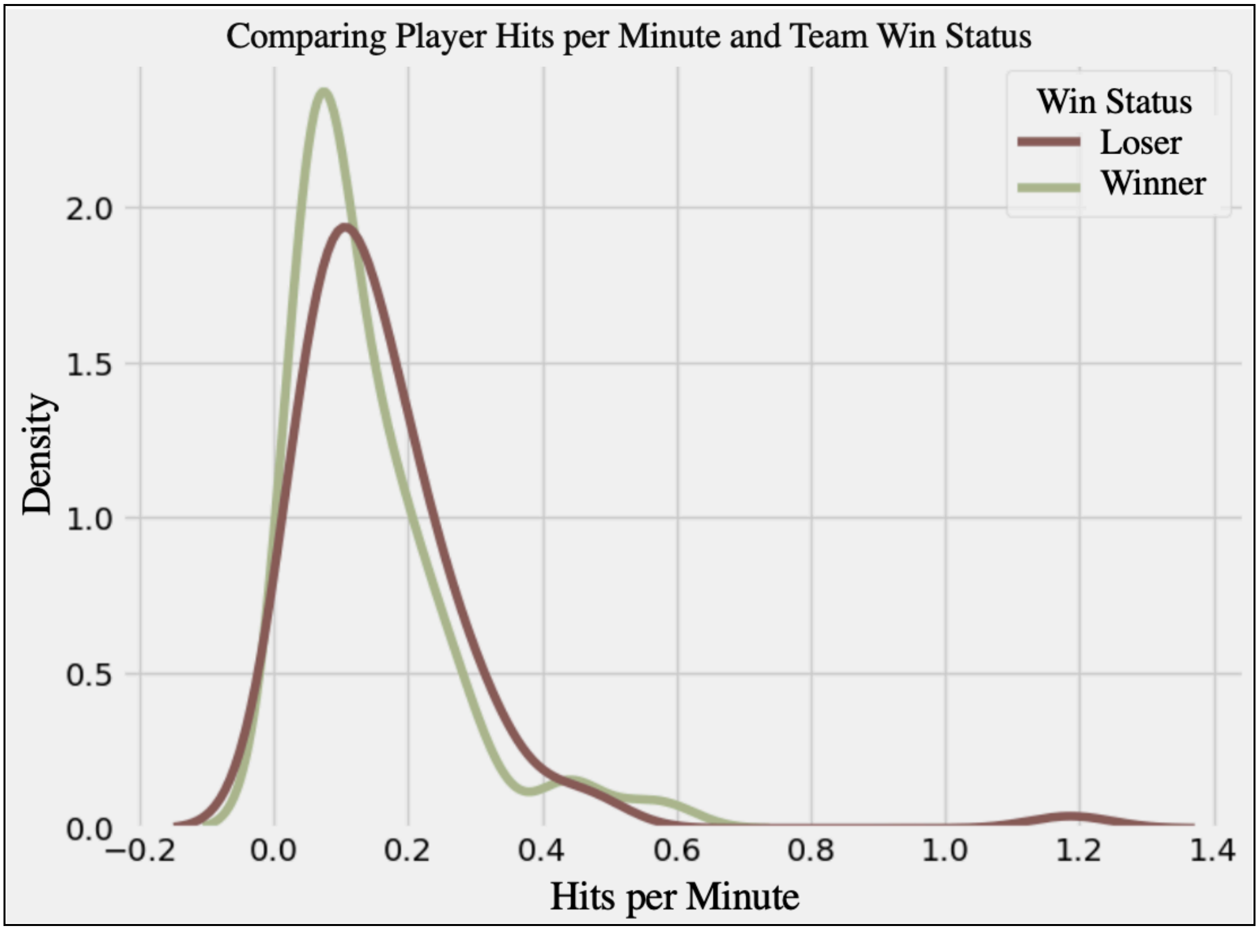


Figure 2 displays the difference in density of hits per minute for each individual player by the team's win status. We found that across the 7 games, there were 166 different players on the ice with at least one hit with an average of 11.9 different players per team per game with at least one hit. Since each player has different play times, we decided to standardize by play time to create the Hits per Minute variable. The figure shows the difference in the spread of the densities among the winning team and losing team.

Figure 3:

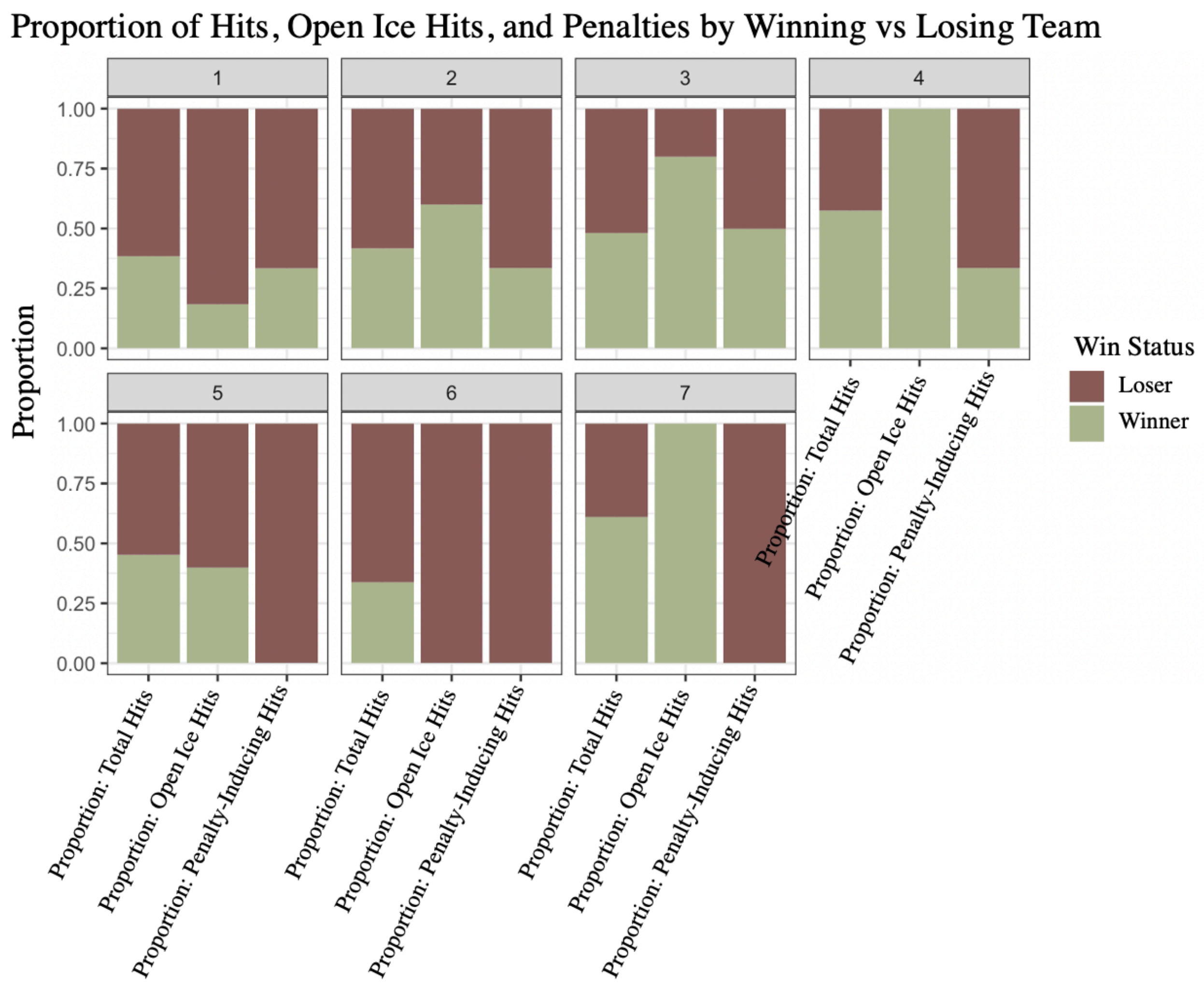


Figure 3 offers a detailed examination of three distinct hit scenarios within hockey gameplay. It highlights - across the seven observed games - the proportion of total hits, open ice hits, and penalties attributed to both the losing team (in red) and the winning team (in green). This breakdown provides insights into how hits contribute to game outcomes and team performance. We calculated these proportions consistently across all three game scenarios, using formulas like the examples below, offering a standardized approach for further analysis:

$$Proportion\ of\ Power\ Play\ Hits\ by\ Winner\ = \frac{\#\ hits\ by\ Winner\ in\ Power\ Plays}{Total\ \#\ Hits\ by\ both\ Winning\ and\ Losing\ Teams}$$

$$Proportion\ of\ Power\ Play\ Hits\ by\ Loser\ = \frac{\#\ hits\ by\ Loser\ in\ Power\ Plays}{Total\ \#\ Hits\ by\ both\ Winning\ and\ Losing\ Teams}$$

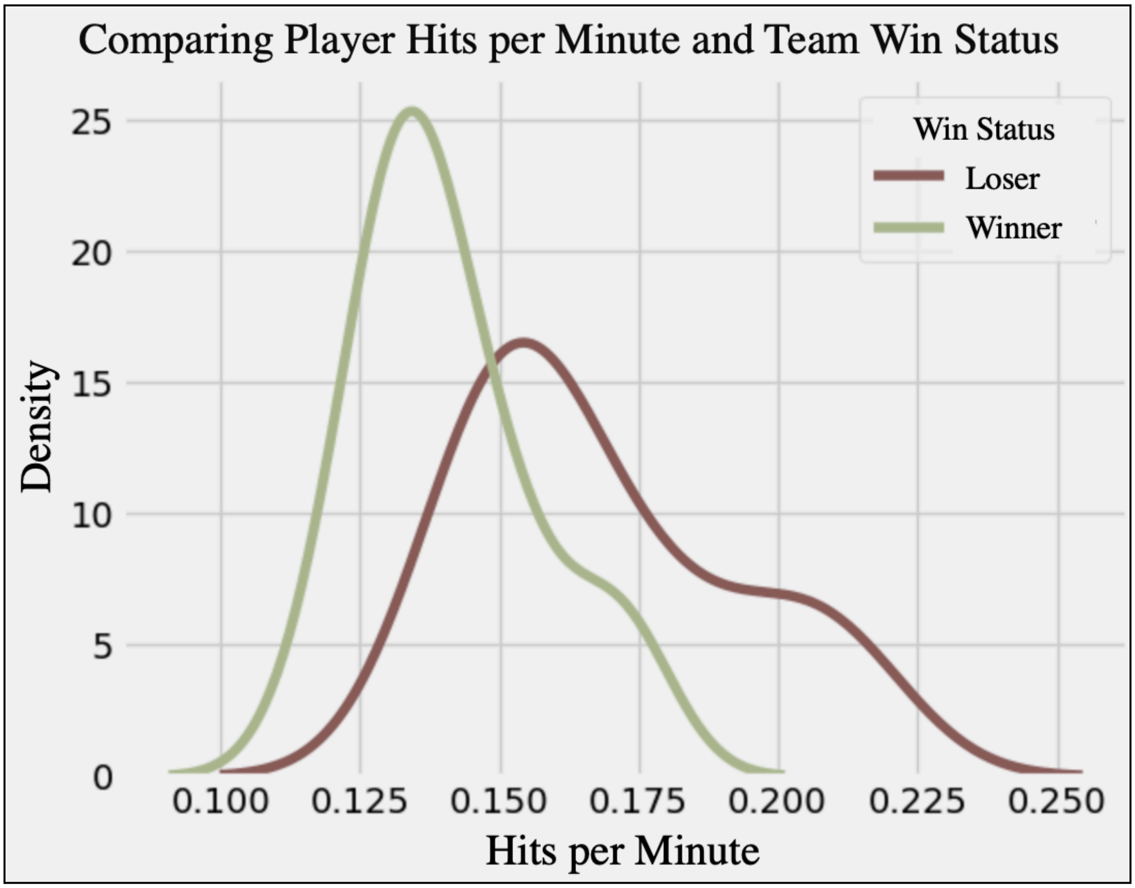
Insights

Spread of Hits:

In an attempt to better understand what goes into a team's success, we decided to delve into individual player's aggression. We aimed to uncover potential disparities in the aggression dynamics between winning and losing teams. For ease of data engineering and to avoid confusion in matching player numbers among the two teams, we first began by splitting the data into players on the home versus away team. We then aggregated hits to the individual player level, found the play time (total and powerplay) for each player on ESPN and merged that with our data, converting times into minutes and seconds. These were all important data-cleaning steps so we would have the most efficient analysis. We then added a column, which represents the hits per minute played by each player and was calculated as follows:

$$Hits\ per\ minute\ =\ \frac{\#\ of\ hits}{total\ play\ time}$$

Looking at Figure 3, it is clear that the losing team typically had more hits in general than the winning team (on average, ~4 more per game), but we were curious to explore where the extra hits were coming from. Were these extra hits coming from a few extremely physical players hitting a lot or do losing teams have a higher number of physical players? This is what led us to make a density plot shown above as Figure 2. Looking at Figure 2, there are subtle but important differences in the spread of the winning and losing teams. First, it appears that the losing team does, on average, have players with a higher number of hits per minute than that of the winning team. Second, the figure highlights the fact that winning teams have a tighter distribution, centered around 0.1 hits per minute while losing teams showed a wider range of aggression levels among players. We employed a t-test to test the validity of this subtle difference in spread and unsurprisingly, we did not find a significant result. This is likely due to the fact that we only had player data from 7 games, which leaves room for our test to be swayed by outliers. To combat this, we decided to try using a bootstrapping technique. Bootstrapping involves generating simulated samples drawn from the original data, offering a means to approximate statistical distributions. We simulated a sample size of 14 games to diminish the influence of outliers while retaining a small sample size, as t-tests are more susceptible to detecting fictional differences in larger samples, which we didn't want to happen. With this new dataset, we recreated the same density graph as seen in Figure 3:



Due to the nature of bootstrapping, we observed an increase in the spread of data for both winning and losing teams. However, a particularly intriguing discovery was the distinct divergence in the peak values between winning and losing teams within our dataset. Furthermore, a notable observation similar to the original graph, was the larger standard deviation in Hits per Minute for losing teams, indicating a wider variation in aggression levels among their players, whereas winning teams exhibited a more tightly clustered distribution around their mean Hits Per Minute. To ascertain the statistical significance of our findings from the bootstrapped dataset, we - once again - conducted a t-test. Our null hypothesis posited that, on average, winning teams had players who were equally or more aggressive than those on losing teams, while the alternative hypothesis suggested the opposite. The resulting p-value from the initial bootstrapped sample was 0.00069, and after doing 100 subsequent resampling iterations consistently all yielded significant p-values, we can confidently assert that, indeed, losing teams exhibit a higher average Hits per Minute compared to winning teams.

While player aggression may intuitively seem like a defensive strategy, aimed at dispossessing the opposing team, our analysis reveals that heightened aggression does not necessarily translate to increased chances of winning. It's worth noting that the majority of hits in hockey do not result in penalties, suggesting that the immediate negative consequences of aggressive play are not readily apparent. This insight prompts a deeper examination of the role of hits in hockey strategy and raises the prospect of strategically managing player aggression to optimize its effectiveness. Furthermore, the psychological aspect of player aggression adds another layer of complexity. When a player's team is losing, there may be a heightened inclination to channel frustration and disappointment into more aggressive play. This suggests that aggression might serve as an outlet for an emotional response to adversity, potentially influencing gameplay dynamics in unforeseen ways. Understanding these psychological nuances could offer valuable insights for coaches and strategists seeking to leverage player aggression in a strategic manner.

Effect of Aggression on the Outcome of the Game:

Understanding the impact of team aggression on game outcomes in hockey holds significant implications for coaches, players, and strategists alike, as it provides valuable insights into the effectiveness of different playing styles and tactics in achieving victory. One of the playing styles we investigated was a team's measurable relative aggressiveness and how it relates to the outcome of a game (win or lose). We started by simply aggregating the number of hits to the game level and splitting the number of hits into the proportion done by the winning team and the proportion done by the losing team. In 5 out of the 7 games our group analyzed, the winning team committed fewer hits than the losing team, meaning the winning team's measurable aggressiveness was lower. The exact proportions of hits delivered by a winning team in the game are as follows:

Game #	Winning Team's Hit Proportion
1	0.4040
2	0.4150
3	0.4000
4	0.5250
5	0.4510
6	0.3390
7	0.6270
Average	0.4515

The proportions for the individual winning teams and the average proportion for all the winning teams were calculated as follows:

$$\frac{Total\ hits\ by\ the\ Winning\ Team}{Total\ Hits\ in\ the\ Game}$$

$$\frac{Average\ Hits\ by\ all\ Winning\ Teams}{Total\ Hits\ in\ all\ Games}$$

Expanding our analysis beyond mere observation, our group explored the realm of predictive modeling, recognizing the potential insights offered by statistical methods. We constructed several logistic regression models, with the binary variable "Winner" indicating whether the home team won or not, while the predictor variables consisted of proportions attributed to the home team. These models were formulated as follows:

1) $Winner\ =\ Proportion\ of\ Hits$
2) $Winner\ =\ Proportion\ of\ Hits\ +\ Proportion\ of\ Power\ Play\ Hits$
3) $Winner\ =\ Proportion\ of\ Power\ Play\ Hits$
4) $Winner\ =\ Proportion\ of\ Hits\ +\ Proportion\ of\ Open\ Ice\ Hits\ +\ Proportion\ of\ Power\ Play\ Hits$

While logistic regression presents advantages in its ability to handle continuous predictor variables (such as proportions) and provide interpretable coefficients, its application to a small sample size necessitates caution. Nonetheless, our results from the logistic regression model offer intriguing insights. Through Leave-One-Out-Cross-Validation (LOOCV), we found that model number 4 exhibited the highest accuracy (with an accuracy of 100%) among all constructed models. LOOCV involves iteratively training the model on all but one data point and evaluating its performance on the omitted data point, providing an estimate of model generalization. This approach is crucial when working with small sample sizes, such as our dataset of 7 games, as it helps provide a more reliable assessment of model performance while using the small dataset to its fullest potential.

Furthermore, the examination of coefficients derived from the optimal model, model number 4, sheds light on the nuanced relationship between team aggression metrics and game outcomes. Given that all predictor variables were inserted as proportions, interpreting the coefficients presents a challenge, as a ‘one-unit’ change signifies a transition from 0% to 100% proportion attributed to that team. However, such extreme transitions are highly improbable in practice, resulting in the analysis of the actual coefficient becoming less informative. Nonetheless, the signs of the coefficients offer valuable insights. Specifically, a lower proportion of total hits and hits on power play are associated with a higher likelihood of winning, whereas a higher proportion of open ice hits is linked to a greater likelihood of winning. This may have to do with the fact that open ice hits are directly related to total hits, thereby creating a multicollinearity issue in the model. To mitigate this concern, we attempted to test a model without the open ice hits variable; however, this alternative model performed worse, highlighting the intricate interplay between these variables and the difficulty in isolating their distinct effects. While definitive conclusions cannot be drawn solely from the coefficients, it is noteworthy that the coefficient on the proportion of total hits variable was roughly 18 times larger than that of the proportion of hits on a power play and 4 times larger than the coefficient for open ice hits. This disparity highlights the potential significance of total hits in influencing game outcomes.

To test our findings further, we decided to do t-tests to test if statistically significant differences existed between the proportion of total hits, proportion of open ice hits, and proportion of power play hits done by the winning team compared to the losing team. Running the tests on our raw data, which included hits from only 7 games, we identified a statistically significant distinction solely in the proportion of power play hits between the winners and losers, resulting in a p-value of 0.01112. To mitigate the constraints imposed by our limited sample size, and possibly uncover important differences, we decided to use a bootstrapping technique. Again, we simulated 14 games and from our bootstrapped sample, we observed a significant difference not only in the proportion of power play hits between the winning and losing teams but saw a significance in total hits as well. Although p-values were not reported due to the stochastic nature of bootstrapping, all differences remained statistically significant across 100 resamples. Interestingly, we did not detect a significant difference in the proportions of open ice hits. This finding may be attributed to the huge variability in the split of open ice hits by winner vs loser. Referring back to Figure 3, we can see this great deal of variability play out among the 7 games.

In conclusion, our investigation into the relationship between team aggression metrics and game outcomes in hockey revealed compelling insights. While logistic regression models provided nuanced understanding, t-tests and bootstrapping techniques augmented our analysis, corroborating the significance of certain aggression metrics in determining game results. Despite challenges posed by sample size limitations, our findings underscore the intricate interplay between aggression levels and victory in hockey, offering valuable implications for strategic decision-making in the sport.

Critiques and Suggestions for Improvement

The primary difficulty we encountered in collecting our observations was the subjective nature of what could be considered a 'hit' in a hockey game. As mentioned prior, we decided that a hit was "an attack that was clearly meant to be aggressive". But as strictly as we can define an 'attack' or 'aggressive' nature, there will always be a natural subjectivity present. This subjectivity stems from the nuanced nature of player interactions on the ice, where individual interpretations vary due to personal perspectives and situational contexts.

While we ultimately didn't utilize the location variable we collected in either of our main analysis questions, we recognize the significance of considering a more detailed breakdown of the ice. Dividing it into potentially 10 (or more) sections, rather than the initial 6, would have offered a more comprehensive perspective on a hit's precise location on the ice. More specifically, we noticed while watching our games that there was a high concentration of hits around and behind the net on both ends of the ice, so we thought that splitting that area into more sections would have been beneficial. Additionally, the division into 10 sections could have led to us using the location variable in our analysis since it would provide more insight. With more specific divisions, we might have recognized a pattern of hits relative to those new divisions that would prompt analysis.

As with any study, having more observations to work from leads to more holistic and extrapolatory conclusions. This is especially present in the analysis and insights from our first research question. While testing our model, we got a 100% accuracy to predict the team that wins, but since we were only testing it against 7 games, it is much easier to get to 100% accuracy than it would be for 700 games. Unfortunately, our ability to validate the model against external data is constrained by the unique variables it incorporates (proportion of total hits, power play hits, and open ice hits), which are not readily accessible online. Thus, expanding the dataset for validation purposes would necessitate manually collecting data. Moreover, it's important to recognize that the model's predictive utility is inherently limited by its reliance on real-time game data. Consequently, while it offers valuable insights into the factors contributing to team success or failure within a specific game, its efficacy as a predictive tool for future outcomes is circumscribed.