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Developing Models to Quantitatively Identify Offensive Player Types in the NHL

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Abstract: The incentives for winning in professional sports cause franchises to find unique competitive advantages that give their team the best shot at finding success. The Moneyball strategy revolutionized the way sports franchises used analytics to increase their team's chance at success by acquiring players that hold the most value to the team and not acquiring players strictly based on their individual performance. In today's game, hockey front offices are consistently trying to implement a Moneyball-like strategy to acquire a player that best meets the needs of the team. In this paper, we developed three unique models for offensive player types in the NHL, to include scorers, net-front scorers, and volume shooters. NHL front offices could adopt each model to identify which offensive players match a team's need to increase their chance of winning.

Keywords: Competitive Advantage, Analytics, Statistical Data

1. Introduction

Front offices in professional sports are finding unique ways to get a competitive advantage over their peers. All of the four main American professional sports (NFL, MLB, NBA, and NHL) have adopted and implemented new strategies in hopes of achieving success in their respective league. The Oakland Athletics of the MLB popularized the use of advanced statistics, and their ideas spread across all major sports. The "Moneyball" strategy of using sabermetrics has ultimately revolutionized the way baseball franchises construct their lineups. Although the small-market Athletics had one of the lowest payrolls in all of the MLB in 2002, they still qualified for the postseason due to the construction of their lineup based on analytics. Michael Lewis, the author of "Moneyball" writes on the use of analytics in baseball, "Managers tend to pick a strategy that is the least likely to fail, rather than to pick a strategy that is most efficient" (Lewis, 2004).

Baseball has seen analytics drive the play of the game. The use of defensive shifts and the introduction of wins above replacement (WAR) has driven lineup and position changes. Basketball has shifted from a game heavily reliant on mid-range jump shooters to a game overwhelmed with three-point shots. Football has seen the rise of hurry-up offenses with the use of the run-pass option which is the offense of choice over the last few decades. However, the use of analytics in hockey has not garnered much attention until recently, as Shea and Baker write "Hockey's complexity means that the analytics revelations won't be so easily uncovered" (Shea & Baker, 2017). The large amount of action that happens in a game paired with low scoring makes hockey a game more difficult to predict than its sister leagues. Low scoring in a hockey game leads to a smaller sample in the response variable then other sports. However, the NHL has more recently began using advanced statistics by implementing new strategies to predict and achieve overall team success.

The use of hockey analytics serves two main purposes: save the front office time by having the evaluation of teams and players readily available and provide decision makers with a unique and novel perspective (Alamar, 2013). Teams in the NHL are using analytics to inform front offices and general managers to best structure a lineup. NHL organizations draft players, sign them from free agency, and trade players regularly to meet the lineup demands of a team. However, a struggle that front offices experience is finding the best players to acquire. If a team loses a high-volume shooter to the salary cap, they are inclined to acquire a replacement volume shooter to fill his role.

There are specific stereotypical playing styles amongst offensive players in the NHL. This paper reveals models using distributions to positively identify three known player types in the NHL: scorers, front-net scorers, and volume shooters. The models for each offensive playing style statistically prove whether the top performers for each playing style are unique from their peers. The literature review consists of a similar use of analytics to analyze player success in professional sports. The methodology includes the overall process of building the model such as building a distribution for each player type using measures such as number of shots and time on ice. The results and analysis show which sets of players are at the end of each distribution. The conclusions and future work section indicate what is significant about each model and how these models can help better inform front offices in decision making.

2. Literature Review

Teams across all major sports are developing unique strategies to apply individual performance to predict a team's success. The use of hockey statistics and analytics is evolving by analysts using more sophisticated metrics to analyze the game and its action. Researchers are challenging standard box score metrics by creating unique ways to assess player performance. Using analytics to assess a players performance stem far beyond basic metrics like shots on goals and plus minus. Like the recent surge in baseball analytics, hockey researchers and front offices hope to create new metrics to analyze players performance to help inform decision making.

2.1 Offensive Scoring Metrics

There are several unique metrics analysts use when assessing an offensive player in hockey that provide a unique scope on a player's performance. There are two major types of offensive statistics: traditional and advanced. Each aid in measuring an offensive player's performance, however analysts utilized traditional measures long before the recent rise in hockey analytics. Analysts tend to favor traditional or advanced metrics based on personal opinion. For example, Dan Demonte, an analyst for the University of Northwestern Sports Analytics Group, is in favor of advanced statistics such as Corsi rating because "[it] helps contextualize a player's worth and contribution to a team, highlighting a good player on a bad team or a bad player on a good team in a way that plus/minus would miss" (Demonte, 2020). However, analyst Mike Commito argues "Plus-minus is the most polarizing statistic in hockey. There's no quicker way to draw battle lines in the hockey community than by starting a dialogue about plus-minus" (Commito, n.d.). Although analysts' perceptions may differ, each type of offensive statistic is valuable in its own regard when assessing player's performance.

2.1.1 Traditional Offensive Scoring Metrics

The use of traditional individual offensive hockey statistics stands the test of time since the beginning of hockey records. These include goals, assists, points, shots on goal, and plus/minus (General Terms, n.d.). Most traditional metrics are intuitive and rather simple but can provide great insight into an offensive players performance. For example, goals allow for analysts to see who mostly contributes to a team's offensive success because teams cannot win games without goals. Shots on goal reveals who is shooting the puck at a high volume and further contributing to an offenses production. Analysts normalize these metrics with a player's time on the ice to show how much production an offensive player generates while he's on the ice. Similarly, plus/minus show how much a player is contributing to his team's success while he's on the ice. The Montreal Canadians developed plus/minus in the 1950's to show the most basic of statistics: how a player contributes to a team's performance while he's on the ice (Vollman, Awad, & Fyffe, 2016). Analysts calculate plus/minus by giving a player a +1 if his team scores a goal while he's on the ice and giving a player a -1 if the opposing team scores while he's on the ice. Coaches want to send out a player with a higher plus/minus because it would increase their chance of scoring and decrease their chance the opponent scoring. However, there limits of using plus/minus. Hockey analyst Neil Greenberg argues "having a good or bad plus/minus rating does not occur in a vacuum. Teammates can and do have a heavy influence in the metric, making it unreliable as a barometer of individual performance" (Greenberg, 2013). As a result, analysts turn to advanced statistics for accurate measure of a player's performance.

2.1.2 Advanced Offensive Scoring Metrics

The growing trend in hockey analytics has led to the rise of advanced metrics, as Tom Awad notes "there has been a revolution in hockey statistics over the last seven years; new statistics are appearing and being used and refined faster than many of us can keep up with" (Vollman, Awad, & Fyffe, 2016). Among these advanced metrics are Corsi ratings and Corsi percentage which replace loopholes presented by plus/minus. Corsi rating is similar to plus/minus only Corsi accounts for shots, blocked shots, and missed shots on top of goals scored. Equation (1) shows the formula for Corsi rating.

$$Corsi = shot\ attempts\ for - shots\ attempts\ against \tag{1}$$

Shot attempts for represent a player shooting the puck for his team and shot attempts against represent the opposing team shooting the puck when that player is on the ice. Corsi percentage represents a Corsi rating as a percentage. Equation (2) shows the formula for Corsi percentage.

$$Corsi\ Percentage = \frac{shot\ attempts\ for}{(shot\ attempts\ for + shot\ attempts\ against)} \tag{2}$$

Also, analysts manipulate Corsi to show success rates. Because Corsi encompasses all facets of shots taken, a success rate is determined to show scored goals out of total shots taken. Equation (3) shows the formula for Corsi Success Rate.

$$Corsi\ Success\ Rate = \frac{Goals\ Scored}{Corsi} \tag{3}$$

Researchers argue Corsi rating is a better overall performance metric than plus/minus because it encompasses much more data points. Because hockey is a low-scoring game, it is difficult to analyze a player's performance strictly off of goals alone (Macdonald, 2012). Corsi rating allows analysts to incorporate more action in a game than plus/minus would, as Corsi incorporates all attempted shots. Analysts average Corsi over a time period to reveal how a player performs at specific time intervals. Aside from Corsi, other advanced statistics in hockey, such as Fenwick rating, are a derivation of traditional scoring but encompasses more action to better predict a player's performance. However, there are pitfalls for Corsi. Hockey analyst David Staples argues "it often leads to unfair and inaccurate judgements. NHL general managers will find this out for themselves if they rely too much on this advance stat metric to make personal decisions" (Staples, 2013). For example, losing teams shoot a much higher percentage of shots late in a game. Although an increase in late-game shot attempts increases a player's Corsi, it hurts their Corsi success rate because a player is taking an abundance of shots potentially without a goal scored.

2.2 Using Traditional Performance Metrics to Forecast Team Success in Hockey

Front offices try to use data and performance metrics to predict the future success of their team. One way to predict a hockey team's success is by using a machine learning approach with statistics. Weissbock, Viktor, and Inkpen attempted to predict a team's success by using luck, much like Corsi, as a performance measure. Due to the high number of events that happen in a game, luck seems to have a bigger impact on the outcome of a hockey game than most other major sports. Luck can be defined as "when the results of the player performance is better (good luck) or worse (bad luck) than the normal average and variance (Weissbock, Viktor, & Inkpen, 2013). Weissbock, Vikrotr, and Inkpen implemented traditional statistics such as goals and performance metrics such as possession and luck into four different machine learning algorithms, to include neural networks and naïve bayes to determine whether an algorithm can predict team success in hockey.

The results of the algorithms indicated that performance metrics, such as luck, was not a large indicator of a team's success. This is likely because luck is by chance, and every team will experience 50% of luck over the course of an infinite number of games. However, using traditional statistics in a neural network, the greatest indicator of single game success was location of the game played and goals against. They concluded that advanced statistics were good indicators of predicting success over the long term while traditional box score statistics are more applicable to short term success (Weissbock, Viktor, & Inkpen, 2013).

2.3 Building WAR Models to Determine Team Success in the NFL

Football analysts are developing multiple ways to model and evaluate an offensive player's performance on the field. Yurko, Ventura, and Horowitz developed a multilevel model to discover how wins above replacement (WAR) contributes to team success by analyzing offensive skill players (Yurko, Ventura, & Horowitz, 2019). They focused on offensive skill players in the NFL, such as quarterbacks, running backs, wide receivers, and tight ends to determine how each respective contribution of an offensive play relates to overall team performance. They modeled each offensive skill player by using nearly every variable possible on a given play. For example, when evaluating a quarterback's performance on a given play "player information includes the passer, targeted receiver, tackler(s), and/or interceptor, along with contextual information about the air yards, yards after catch, pass location, and if the passer was hit on the play" (Yurko, Ventura, & Horowitz, 2019). They used a mathematical model for each of the offensive player types to determine the proportion of offensive plays a player is involved in. (Yurko, Ventura, & Horowitz, 2019). They turned the proportion of plays an offensive player is involved in into three overall categories of WAR: passing, receiving yards after catch, and rushing by using a mathematical model to calculate WAR from a player's involvement and success rate. They used these three statistics based on their ability to most accurately

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model how well an offensive skill player is performing (Yurko, Ventura, & Horowitz, 2019). Ultimately, the three categories of WAR show how valuable a player is to a team's performance and contributes to overall team success.

Yurko, Ventura, and Horowitz's contributions help identify how offensive skill players contribute to team success. They concluded that a quarterback has a much larger range than any other offensive position. This indicates that the quarterback position has the largest impact on the potential team success and the outcome of a game. Because this position heavily impacts a team's success, teams are more inclined to acquire and play the best quarterback possible. Front offices are able to use this model to determine what offensive players contribute the most team success.

3. Methodology

Using official data from the 2018-2019 NHL season, we developed three models for each respective offensive player type: scorers, net-front scorers, and volume shooters. The primary purpose of each model is to quantitatively identify all three hypothesized offensive stereotypes in the NHL by developing models and statistically proving each model's accuracy. We gathered all data from Evolving Hockey's database, manipulated the data in Microsoft Excel, and statistically drew conclusions using Minitab. We only developed models for offensive positions including left wing, right wing, and center, as we did not include defensemen in each model. The models only consider when a game is a five-on-five. Power plays enhance the man-up team's offensive player's chance to score, so the models exclude power plays. Every player qualifies for each model pending they meet the minimum requirements for the model. For example, a player identified as a scorer could also identify as a volume shooter in each respective model if they fall under the end of the distributions for each model.

3.1 Scorers

The first model we developed was for scorers. Scorers are known best for their ability to score from almost anywhere on the ice. Naturally, a scorer possesses a shot-first mentality, as he can and does get the puck to the net at a high rate with the ability to beat the goalie with his shot. Front offices in the NHL sign scorers due to their ability to produce and carry the team on the offensive side of the ice. Therefore, we used Corsi success rate to best quantify a player who constitutes as a scorer because it reveals who attempts a large number of shots and converts in the NHL. To determine Corsi success rate, we solved for Corsi by summing each player's total shots, blocked shots, missed shots, and goals. Then, we divided each player's goals scored over their Corsi. The model only included players with over thirty games played to provide enough data for an accurate model.

To better explain how we calculated Corsi success rate for each offensive player, we will use Jake Guentzel as an example. As a center in one of the top offensive teams the NHL, Guentzel scores often. To build a model to prove he is a scorer, we calculated his Corsi for every game he played in during the 2018-2019 season. Guentzel's Corsi success rate was determined by dividing his scored goals by his Corsi. Guentzel yields a 14.18 Corsi success rate, which is second highest overall percentage in our model. Guenztel's high Corsi success rate stems from his high number of goals scored compared to his overall Corsi while on the offensive. Figure 1 shows the distribution and summary statistics for every player encompassed in the model for scorers. The distribution below shows normally distributed data based off of the 397 offensive players who meet the minimum criteria. Ultimately, our model aimed to find players at the upper end of the distribution of players as scorers.

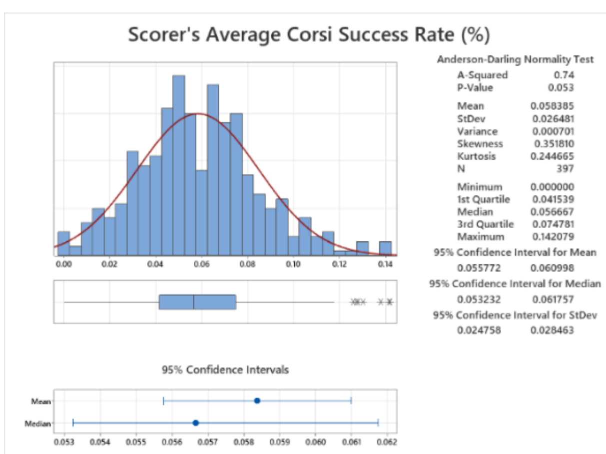

Figure 1. Distribution of Scorers *(Play by Play Past Games Query, 2021).*

3.2 Net-Front Scorers

Net-front scorers are highly dangerous scoring threats within eight feet of the net. They are known best for their scoring touch around the net, to include shooting, deking, and deflecting, rather than their ability to beat the goalie from distance with their shot. Net-front scorers provide a net-front offensive presence on a line. They encompass the same basis for scorers, however the model for net-front scorers only factors goals scored inside of eight feet. We used Corsi success rate, like the model for scoring, as a basis for the scoring metric while limiting the model to goals scored inside of eight feet. Like scorers, the model only encompasses players who played in at least thirty games. Because the net-front scorer model only includes shots taken from close range, the Corsi success rate is destined to increase, as the chances of scoring closer to the net increase. Figure 2 shows the distribution and summary statistics based on average Corsi success rate within eight feet of the net for every offensive player in the 2018-2019 season. The distribution shows non-normally distributed data based off of 263 offensive players who meet the minimum criteria. The median is at the upper end of the range which indicates there are a large number of players who did not meet the criteria for representation in the model.

3.3 Volume Shooters

A volume shooter represented in this model is an offense player that frequently shoots the puck at the net. The role of the volume shooter to his team is to constantly take shots from anywhere on the ice to give his team the offensive advantage. In our model, we identified volume shooters using Corsi for per twenty minutes played. This encompasses an offensive player's average Corsi over a twenty-minute span; this includes the total number of blocked shots, goals, and missed shots. If a player takes more shots than his peers, his Corsi for per twenty will ultimately increase as a result. We chose twenty minutes rather than a full sixty-minute game because it shows a more condensed trend for offensive players to attempt shots. Twenty minutes is still long enough to show a significant amount of Corsi contribution, but it still more represents a player's overall time spent on ice during a full game. Figure 3 shows the distribution and summary statistics based on the average Corsi for per twenty for every offensive player of the 2018-2019 season. With a p-value less than 0.005 for an Anderson-Darling Normality Test, we can conclude that the distribution for net-front scorers is normally distributed. Players with Corsi for per twenty above the third quartile have a much larger range than each of the other three quartiles which is where we found the majority of the volume shooters.

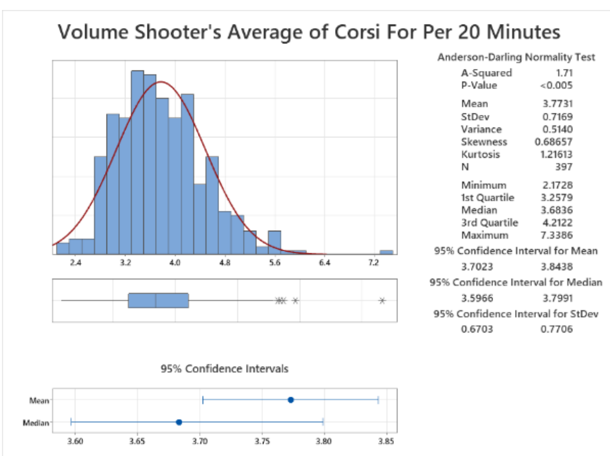

Figure 2. Distribution of Net-Front Scorers *(Play by Play Past Games Query, 2021).*

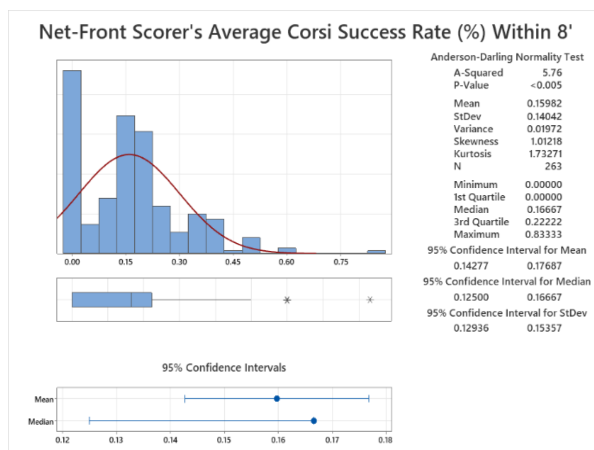

Figure 3. Distribution of Volume Shooters *(Play by Play Past Games Query, 2021).*

4. Results

Each model produced a wide variety of different results that applies to various uses. Each model identified offensive players as scorers, net-front scorers, and volume shooters as a small subset from each respective model's distribution. For example, only twenty-nine players are volume shooters from the total population of 199 players. The model for scorers was the only model that provided data that was normally distributed. As a result, we ran a two-sample t-test to determine that fifteen identified scorers were statistically independent from the rest of the population. The models from net-front scorers and volume shooters were not normally distributed. Therefore, we ran a nonparametric mood's median test to statistically prove how net-front scorers and volume shooters are independent from the rest of their respective populations. A list of the top ten scorers, net-front scorers, and volume shooters were determined based off our statistical results.

4.1 Scorers

Using Corsi success rate as the metric, we identified a total of fifteen scorers out of a total population of 397 players. We identified Scorers as two standard deviations above the mean Corsi success rate of 5.84%, as the standard deviation is 2.65%. Therefore, we identified any player with a Corsi success rate greater than 11.14% as scorers. To test whether the scorer's population is statistically significant against the rest of the population, we ran a two-sample t-test with the following hypotheses:

$$H_0 = The\ Difference\ in\ population\ means\ for\ Scorers\ and\ Non\ Scorers = 0$$
$$H_A = The\ Difference\ in\ population\ means\ for\ Scorers\ and\ Non\ Scorers \neq 0$$

With a p-value of 0.00, we rejected the null hypothesis in favor of the alternative hypothesis that scorer's Corsi success rate is statistically separate than that of the rest of the qualifying offensive players. Figure 4 shows a histogram with the Corsi success rate of Scorers compared to the rest of the population, and Table 1 shows a list of the top ten scorers.

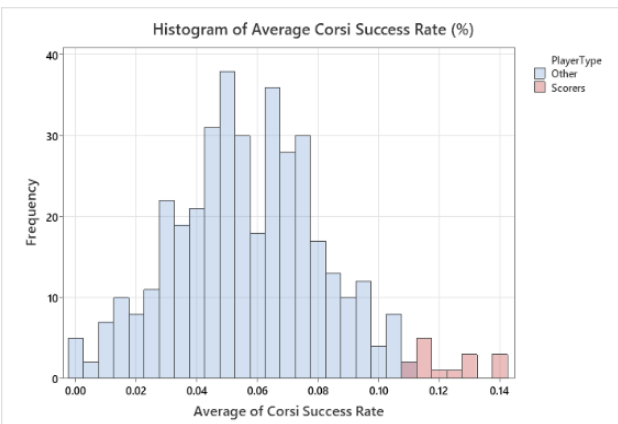

Figure 4. Histogram of Scorers vs Non-Scorers

Table 1. Top 10 Scorers in the NHL in the 2018-2019 Season Based on Corsi Success Rate (%)

Player Name	*%*
1. Leon Draisaitl	14.21
2. Jake Guentzel	14.18
3. Michael Amadio	13.81
4. Tyler Ennis	13.03
5. Cody Eakin	12.80
6. Brian Gibbons	12.76
7. Matt Duchene	12.61
8. Chandler Stephenson	11.76
9. Ivan Barbashev	11.67
10. Joe Pavelski	11.64

4.2 Net-Front Scorers

We used a different statistical method from scorers for net-front scorers because the distribution for net-front scorers is not normal. Using Corsi success rate within eight feet as the metric, we identified twenty-eight offensive players out of a total population of 263. Similar to scorers, we identified players with two standard deviations above the mean of 15.88% as net-front scorers. With a standard deviation of 14.04%, a total of twenty-eight players made the cut. To statistically prove whether these twenty-eight players identified as net-front scorers are statistically different from the rest of their population, we ran a Mood's median test with the following hypotheses:

$$H_0 = The\ Difference\ in\ population\ medians\ for\ Net - Front\ Scorers\ and\ Non\ Net - Front\ Scorers = 0$$
$$H_A = The\ Difference\ in\ population\ medians\ for\ Net - Front\ Scorers\ and\ Non\ Net - Front\ Scorers \neq 0$$

The Mood's median test yielded a p-value of 0.00 indicating the rejection of the null hypothesis in favor of the alternative hypothesis. Therefore, we concluded that the population of twenty-eight net-front scorers were statistically different from the rest of the population. Figure 5 shows a histogram of with the Corsi success rate inside 8' of net-front scorers compared to the rest of the population, and Table 2 shows a list of the top 10 net-front scorers.

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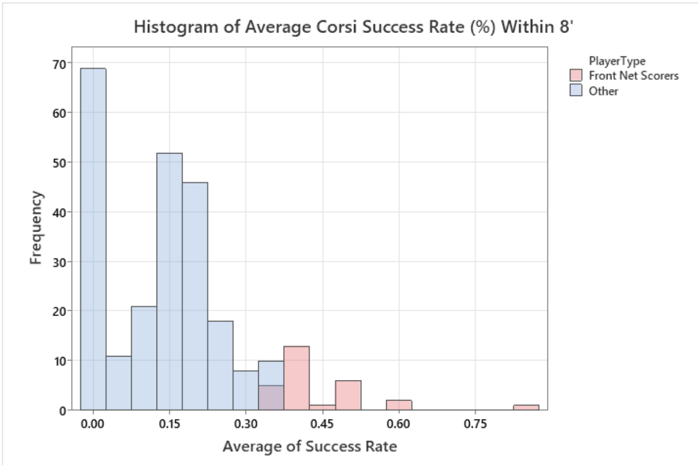

Figure 5. Histogram of Net-Front Scorers vs Non-Net-Front Scorers

Table 2. Top 10 Net-Front Scorers in the NHL in the 2018-2019 Season Based on Corsi Success Rate (%) Within 8'

Player Name	*%*
1. Chris Kreider	83
2. Alex Galchenyuk	60
3. Mats Zuccarello	60
4. Anze Kopitar	60
5. Jason Pominville	50
6. Brian Boyle	50
7. Tomas Tatar	50
8. William Karlsson	50
9. Thomas Vanek	50
10. Matt Duchene	46

4.3 Volume Shooters

The statistical method used for volume shooters is very similar to net-front scorers due to the non-normal distribution of Corsi for per twenty minutes. We identified a total of twenty-nine volume shooters from a population of 397 players. This was because their Corsi for per twenty at least two standard deviations above the mean of 3.77 and the standard deviation of 0.72. The number of players tagged as volume shooters is very similar to the number of players tagged as net-front scorers, although we did not conduct any tests to see if these two groups of players were correlated. To statistically prove whether these twenty-eight players identified as volume shooters are statistically different from the rest of their population, we conducted a mood's median test with the following hypotheses:

$$H_0 = The\ Difference\ in\ population\ medians\ for\ Volume\ Shooters\ and\ Non-Volume\ Shooters = 0$$
$$H_A = The\ Difference\ in\ population\ medians\ for\ Volume\ Shooters\ and\ Non-Volume\ Shooters \neq 0$$

The mood's median test yielded a p-value of 0.00 indicating the rejection of the null hypothesis in favor of the alternative hypothesis. Therefore, we concluded that the population of twenty-nine volume shooters were statistically different from the rest of the population. Figure 6 shows a histogram of with the Corsi for per twenty of volume shooters compared to the rest of the population, and Table 3 shows a list of the top ten volume shooters.

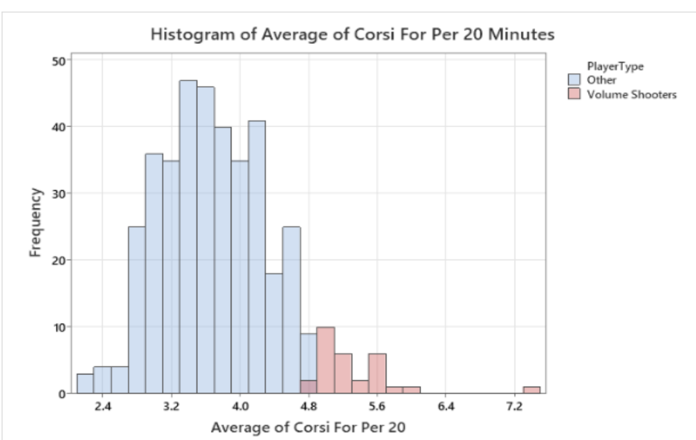

Figure 6. Histogram of Volume Shooters vs Non-Volume Shooters

Table 3. Top 10 Volume Shooters in the NHL in the 2018-2019 Season Based on Corsi For Per 20 Minutes

Player Name	*%*
1. Brenden Gallagher	7.34
2. Garrett Wilson	5.94
3. Rocco Grimaldi	5.74
4. Brenden Perlini	5.70
5. Kyle Clifford	5.65
6. Timo Meier	5.58
7. Dmitrij Jaskin	5.56
8. Ryan Donato	5.52
9. Daniel Sprong	5.50
10. Miles Wood	5.47

5. Conclusion

The research proposes three models for quantitively identifying offensive player types in the NHL. Three of the most unique and important offensive skills a hockey player possesses is the ability to score, the ability to score in close proximity to the net, and the ability to constantly attempt shots. Our models incorporate Corsi metrics molded specifically for each offensive player type. Most traditional hockey metrics that measure offensive skills are flawed because they fail to accurately depict a player's performance without taking into account of his team and his opposition. However, using advanced offensive scoring metrics, our models produce names of offensive players where NHL front office personnel confirmed their playing type from each model. For example, after showing the results for the scorer's model, NHL front office personnel overwhelmingly agreed that the identified scorers are indeed natural scorers who possess the ability to score from anywhere on the ice. NHL front offices could adopt the models to reveal who the top players are in each model rather than relying on traditional scoring metric's capability of flawed results.

Like many professional sports, the salary cap constrains teams in the NHL, and other factors create a constrained environment where front offices build a roster with limited resources. Coaches and managers are inclined to find players to address the needs of the team. Our research would help front offices identify players who are proven scorers, front-net scorers, or volume shooters that other NHL teams do not seek in the free agency market. It is impossible for front offices to acquire or draft any player available because the salary cap restrains their spending on players. For example, the Columbus Blue Jacket's insider Jeff Svoboda wrote in an article after the 2020-2021 season that one of the biggest uncertainty the Blue Jackets faced going into their next season was presence at the Centre position (Svoboda, 2021). Because the Blue Jackets only had about $26 million to spend with salary cap constraints, they could use the models to find proven scorers, front-net scorers, or volume shooters who fly under the radar from other NHL teams in free agency (Svoboda, 2021). To create a complete offensive roster, one could build off our research by incorporating assist data to compliment a team with players who can move the puck on the ice on the offensive end. This would provide front offices with the ability to find players who meet the needs of their team for every offensive position on the ice.

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