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Shot by Shot: A Statistical Deconstruction of Logan Couture's Career

Introduction

How has recent retiree Logan Couture's personal shot profile, characterized by close-range, quick-release scoring, both reflected and influenced the San Jose Sharks' evolving offensive strategies from 2007 to 2022? Through the spatial analysis of goal locations, shot types, and shooting efficiency across four team eras, I evaluate the synergy between Couture's tendencies and broader tactical team shifts. To quantify scoring likelihood, a predictive model was also developed to estimate goal probability based on shot characteristics, demonstrating an applied machine learning approach to hockey analytics. Additionally, I introduce a suite of custom performance metrics to isolate and contextualize what set Couture apart from his team, including his timing, positioning, efficiency, and decision making under pressure.

Sharks Data Overview and Exploratory Data Analysis

For the purposes of further analysis, the 2007–2022 NHL seasons were divided into four distinct eras. I will examine the eras through the context of the evolution of the San Jose Sharks hockey team.

1. Early Contention Era (2007–2010):
   This period marked the emergence of the Sharks as consistent playoff contenders, with a strong core of veteran players along with a multitude of high seed finishes in the regular season.

2. Transition Era (2011–2014):
   These seasons reflected a period of change in the team's roster and leadership; younger players began to take on larger roles and the team experienced inconsistent playoff outcomes.

3. Cup Run Era (2015–2018):
   This era was the most successful of the four, highlighted by a Stanley Cup Final appearance in 2016.

4. Rebuilding Era (2019–2022):
   Following the apex of the Sharks, this period is characterized by a decline in game results, aging core players, and the beginning of a roster transition and rebuild strategy.

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To examine changes in the San Jose Sharks' offensive tendencies over time, I examined the usage of shot types and spatial distribution across these four defined eras between 2007 and 2022. This analysis incorporates both heat map visualizations of goal locations and summary statistics that include total shots, goal counts, average shot distances, and shooting percentages for each shot type.

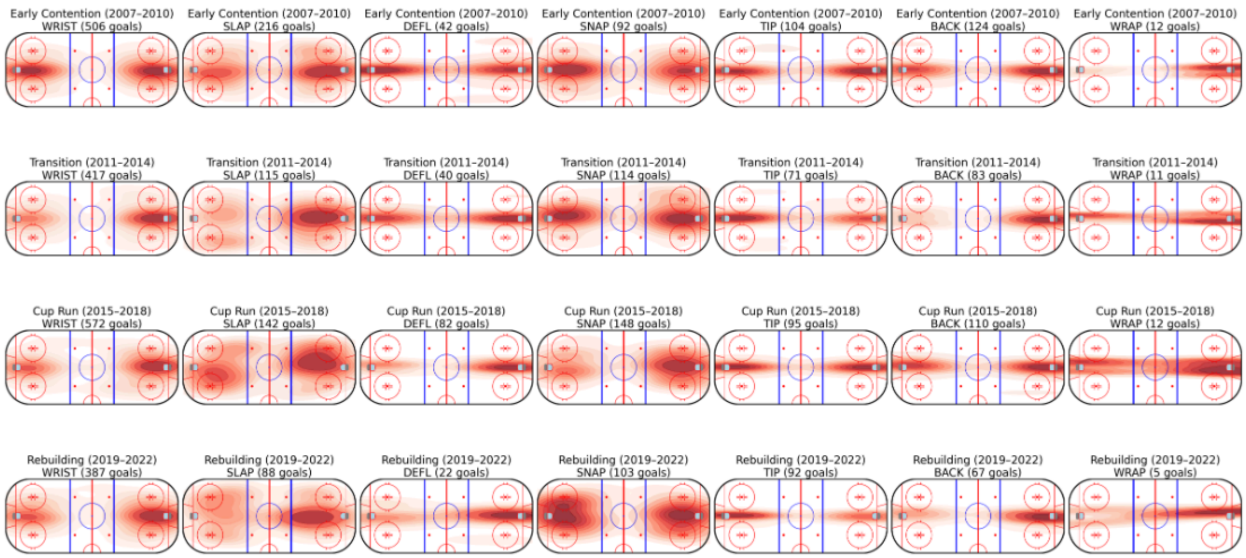

Figure 1

Early Contention (2007–2010) Shot Summary

	ShotType	TotalShots	GoalCount	AvgShotDistance	ShootingPercentage
0	SLAP	4801	216	32.83	4.50
1	SNAP	1464	92	24.32	6.28
2	WRIST	7977	506	22.61	6.34
3	TIP	1038	104	15.54	10.02
4	BACK	1327	124	12.76	9.34
5	WRAP	265	12	6.19	4.53
6	DEFL	358	42	13.28	11.73

Transition (2011–2014) Shot Summary

	ShotType	TotalShots	GoalCount	AvgShotDistance	ShootingPercentage
0	WRIST	7500	417	21.84	5.56
1	TIP	793	71	17.21	8.95
2	SLAP	3211	115	37.19	3.58
3	WRAP	172	11	5.34	6.40
4	BACK	1155	83	12.34	7.19
5	SNAP	1489	114	27.52	7.66
6	DEFL	435	40	12.07	9.20

Cup Run (2015–2018) Shot Summary

	ShotType	TotalShots	GoalCount	AvgShotDistance	ShootingPercentage
0	WRIST	8876	572	25.09	6.44
1	BACK	1231	110	13.02	8.94
2	DEFL	913	82	15.21	8.98
3	SNAP	1854	148	27.60	7.98
4	TIP	1148	95	13.77	8.28
5	SLAP	2981	142	36.34	4.76
6	WRAP	203	12	7.37	5.91

Rebuilding (2019–2022) Shot Summary

	ShotType	TotalShots	GoalCount	AvgShotDistance	ShootingPercentage
0	WRIST	6721	387	23.82	5.76
1	TIP	1148	92	12.38	8.01
2	SLAP	1561	88	38.76	5.64
3	WRAP	175	5	7.28	2.86
4	SNAP	1143	103	26.69	9.01
5	BACK	904	67	11.37	7.41
6	DEFL	201	22	14.91	10.95

Figure 2

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Figure 2 denotes that the most noticeable trend over time is the decline in both the use and effectiveness of slap shots, accompanied by an increase in shot distance. In the earliest era, slapshots accounted for over 1,400 attempts with a shooting percentage of 4.5%. By the Rebuilding era (2019-2022), that number had dropped to under 600 attempts with the efficiency falling under 3.1%. This decline demonstrates a strategic move to move away from long-distance attempts toward quicker release shots taken closer to the net.

Wrist and snap shots consistently represent the most effective and frequently used shot types. Wrist shots produced the highest goal totals across all eras, particularly during the team's most competitive phase (2015–2018). Snap shots demonstrated rising usage and peaked in shooting efficiency during this same period. Figure 1 reveals that both of these shot types are predominantly taken from high-danger areas in front of the net, which reinforces their role as the team's primary scoring strategy. Compared to the previous era, deflection goals more than doubled during the Sharks' Cup Run, with a 105% increase in goals and a 110% increase in attempts. This highlights a deliberate shift toward net-front scoring tactics.

The close-range shot types such as backhands, tips, and wraparounds maintained relatively consistent patterns across eras. While these shot types were used less frequently, they were generally more efficient in converting attempts into goals. For instance, deflections had some of the highest shooting percentages in the dataset, indicating their value in opportunistic, net-front situations.

Overall, the average distance of goals by shot type further illustrates a strategic evolution in shooting. Long-range shots like slap shots remained less effective, while close-range and quick-release shot types became increasingly emphasized. These findings suggest a gradual shift in the Sharks' offensive approach toward maximizing efficiency by prioritizing shot types and locations with higher scoring probabilities.

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Early Contention (2007–2010) Shot Summary (League-Wide)

	ShotType	TotalShots	GoalCount	AvgShotDistance	ShootingPercentage
0	WRIST	190226	13479	21.53	7.09
1	BACK	33310	2946	14.26	8.84
2	SLAP	113052	4339	41.83	3.84
3	TIP	26084	3080	14.02	11.81
4	SNAP	63524	4265	25.51	6.71
5	WRAP	5070	258	8.07	5.09
6	DEFL	7280	754	15.21	10.36

Transition (2011–2014) Shot Summary (League-Wide)

	ShotType	TotalShots	GoalCount	AvgShotDistance	ShootingPercentage
0	SNAP	53855	3751	25.55	6.96
1	WRIST	189765	12305	21.72	6.48
2	SLAP	86847	3278	41.55	3.77
3	TIP	21691	2365	13.68	10.90
4	BACK	30446	2458	13.17	8.07
5	DEFL	8262	845	14.48	10.23
6	WRAP	4258	213	7.83	5.00

Cup Run (2015–2018) Shot Summary (League-Wide)

	ShotType	TotalShots	GoalCount	AvgShotDistance	ShootingPercentage
0	BACK	34443	2863	13.54	8.31
1	SNAP	64768	4529	26.12	6.99
2	WRIST	234219	15290	23.25	6.53
3	TIP	29514	2923	13.45	9.90
4	WRAP	4185	232	8.15	5.54
5	SLAP	80600	3326	40.24	4.13
6	DEFL	9925	913	15.54	9.20

Rebuilding (2019–2022) Shot Summary (League-Wide)

	ShotType	TotalShots	GoalCount	AvgShotDistance	ShootingPercentage
0	WRIST	232296	15397	23.23	6.63
1	SLAP	59080	2901	38.15	4.91
2	TIP	30811	2895	13.00	9.40
3	SNAP	57916	4864	25.13	8.40
4	BACK	31297	2754	12.54	8.80
5	WRAP	3690	194	7.25	5.26
6	DEFL	10241	923	14.73	9.01

Figure 3

To put the San Jose Sharks' shooting tendencies into context, I compared them to league-wide shot data across the same eras (Figure 3). While the overall league followed similar trends, such as the decline in slap shots and a growing reliance on wrist and snap shots, the magnitude of these changes varied. For instance, league-wide slap shot usage declined but remained more prevalent than it did for the Sharks, who phased it out more aggressively. Similarly, while wrist shots consistently led goal production league-wide, the Sharks' dependence on them was much more pronounced. The average shot distances and shooting percentages by shot type also suggest that the Sharks' offensive strategies were more conservative, especially in the later eras.

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Logan Couture Data Overview and Exploratory Data Analysis

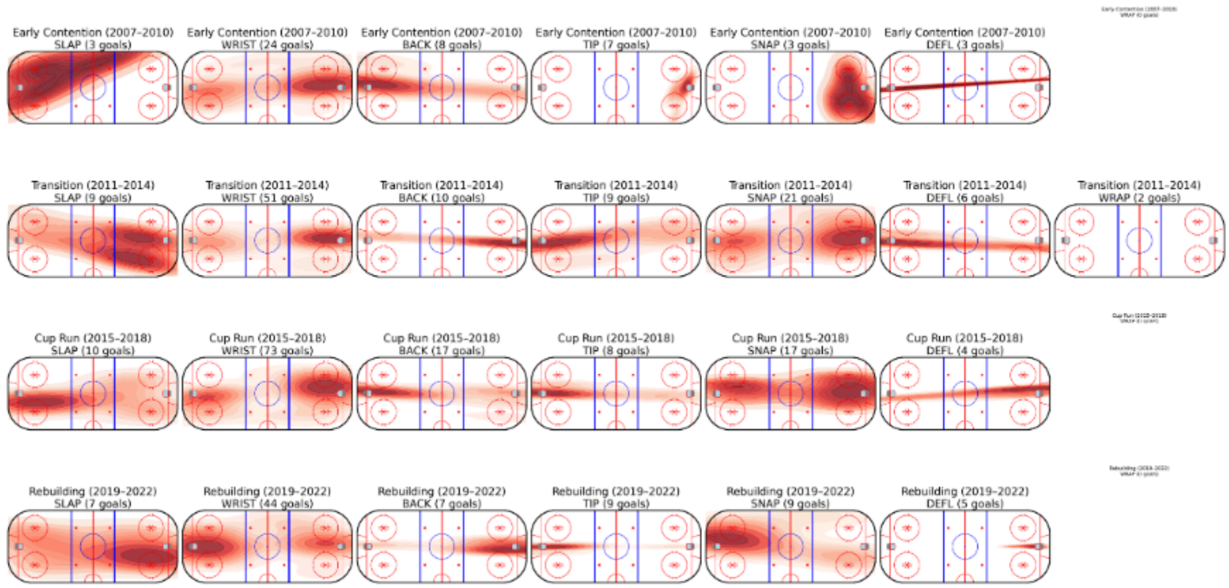

Figure 4

Figure 4 clearly shows from the start of his career, Couture focused on higher-danger areas in the slot, using wrist and snapshots while avoiding higher risk shots such as the slapshot. Rather than adapting to a changing league, the league seemed to adapt to the style of Couture. Although it may be too definitive to say he engineered the strategy completely, his scoring profile clearly aligned with and influenced the team's overall broader tactical shift.

Exploratory Data Analysis – Shot Style Drift Score

To quantify how much the Shark's and Couture's shot selection profile evolved over time, I developed the Shot Style Drift Score (SSDS). This metric measures the amount of change in the distribution of shot types (e.g., wrist, snap, slap, deflection, etc.) from one team era to the next. For each era, I calculated the proportion of total shots that each shot type represented. The SSDS is computed as the sum of the absolute differences in their proportions between consecutive eras. This captures the extent to which a player's/team's shooting tendencies shifted over time. A higher SSDS indicates a more significant transformation in shot style.

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from_to	DriftScore_Couture	DriftScore_Team
Early Contention (2007-2010) → Transition (2011-2014)	0.176036	0.228771
Transition (2011-2014) → Cup Run (2015-2018)	0.131892	0.308596
Cup Run (2015-2018) → Rebuilding (2019-2022)	0.194655	0.214408

Figure 5

Couture's SSDS reveals a relatively stable shot selection strategy compared to the rest of the team. He maintained a very consistent shot profile during the team's rise to competitiveness, whereas his team underwent its most significant tactical shift during this same period. Couture's gradual shot style drift implies that he did less evolving than his team. This further supports the idea that the team adjusted to Couture's tactics rather than vice versa.

Methodology – Predictive Model

My models predict the probability that a given shot results in a goal using over 80 unique features derived from NHL game data from 2007 to 2022. They incorporate a variety of detailed information such as shot-type, player, and team context variables. By capturing shooting patterns in the NHL, the models' generate expected goals estimates for each shot that the Sharks take.

The logistic regression models the relationship between the input features and the likelihood of a shot becoming a goal by applying the sigmoid function to a linear combination of the inputs, resulting in a probability between 0 and 1. The random forest model estimates the probability by ensembling multiple decision trees, each trained on different subsets of data, to capture non-linear relationships between the input features and outcomes. The XGBoost model predicts the probability by constructing multiple decision trees that iteratively focus on correcting the prior trees in order to capture non-linear patterns.

For testing purposes the data was split into a training and testing split and the ROC-AUC and PR-AUC were calculated. The ROC-AUC measures the ability of a model to distinguish between goals and non-goals across all classification thresholds, plotting the true positive rate against the false positive rate. A higher ROC-AUC shows better overall discrimination, but in an imbalanced dataset (where goals are much rarer than non-goals), the ROC-AUC can be too optimistic. The PR-AUC addresses this issue by focusing on the goals, measuring the trade-off between precision (how many predicted goals were correct) and recall (how many actual goals were detected.

Figure 6 demonstrates the testing results of the three models before hyperparameters have been tuned.

```
Random Forest ROC-AUC: 0.9708
Random Forest PR-AUC: 0.6489

XGBoost ROC-AUC: 0.9751
XGBoost PR-AUC: 0.7125

Logistic Regression ROC-AUC: 0.9192
Logistic Regression PR-AUC: 0.4172
```

Figure 6

Methodology - Tuning Model Hyperparameters

For all models, I defined a comprehensive hyperparameter grid and applied a randomized search with 3-fold cross-validation and 10 sampled parameter combinations. The models were evaluated using average precision (PR-AUC) as the scoring metric, which, as mentioned prior, is well-suited for imbalanced classification tasks like goal prediction.

For the logistic regression, hyperparameters consist of regularization type, strength, and solver. The two types of regularization tested were the L1 penalty (lasso) which can push some coefficients to 0 and is therefore useful for feature selection, and the L2 penalty (ridge) which shrinks coefficients towards 0 but does not eliminate them. I chose five values of strength with a range of high and low penalties. I used two optimization methods that support both the L1 and L2 penalties. The first method, liblinear optimization, uses coordinate descent to solve one weight at a time efficiently. The second method, saga, uses Stochastic Average Gradient Descent which is a randomized and scalable algorithm that works well with large datasets and high-dimensional features.

For the Random Forest model, hyperparameters consisted of the number of trees, tree depth, node splitting criteria, and class weighting. I tested numerous values for the number of estimators, which determines the number of trees in the forest. This balances performance with computational costs. To regulate the model complexity and prevent overfitting, I tuned the max depth, which limits how deep each individual tree can grow. I also adjusted the minimum number of samples required to split a node and also to be a leaf node. These parameters help generalize the model such that it does not overfit to noise in the data. For feature selection, I used two metrics for the maximum features which limits the number of features considered when making a split. Finally, I set the class weight to balanced to compensate for the class imbalance in goal prediction.

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For the XGBoost model, hyperparameters tuned included the number of trees, tree depth, learning rate, subsampling parameters, and class weighting. I changed the number of estimators to control the number of boosted trees that are sequentially added to the model. More trees allowed for better performance, but at the cost of increased training time. To manage the complexity of the model I tuned the maximum tree depth, which controls how deep each tree can grow to help prevent overfitting. I also adjusted the learning rate to control the contribution of each tree; smaller values allow for more gradual learning and can improve overall generalization when combined with a higher number of trees. In addition, I tuned the subsample and colsample_bytree which randomly samples rows and features, respectively, in order to reduce variance. Finally, I adjusted the scale_pos_weight parameter to address class imbalance by making the importance of the minority class (goals) larger during training.

```
Best parameters for Logistic Regression:
{'solver': 'liblinear', 'penalty': 'l2', 'C': 100}
Logistic Regression ROC-AUC: 0.9175
Logistic Regression PR-AUC: 0.4680


Best parameters for Random Forest:
{'n_estimators': 500, 'min_samples_split': 5, 'min_samples_leaf': 2, 'max_features': 'sqrt', 'max_depth': 40, 'class_weight': N
one}
Random Forest ROC-AUC: 0.9733
Random Forest PR-AUC: 0.6902


Best parameters for XGBoost:
{'subsample': 0.7, 'scale_pos_weight': 1, 'n_estimators': 300, 'max_depth': 6, 'learning_rate': 0.01, 'colsample_bytree': 0.7}
XGBoost ROC-AUC: 0.9761
XGBoost PR-AUC: 0.7247
```

Figure 7

Figure 7 denotes the best parameters used for each model after the application of the grid search and showcases a significant increase in the ROC-AUC and PR-AUC to the pre-tuned models.

Logan Couture Expected Goals

I quantified Couture's shot quality over time by comparing his averaged expected goals per shot to the teams' across all four eras. In every single era, Couture's expected goal per shot exceeded the team's average. This consistently higher expected goal metric reflects his focus on generating dangerous scoring changes from high-probability areas. These results demonstrate his role as a skilled finisher with shot selection that aligned with the team's evolving offensive strategy. It is important to note that players that play positions such as defense are less likely to take shots from higher danger areas.

	Era	Couture xG/Shot	Team xG/Shot
0	Early Contention (2007–2010)	0.0823	0.0672
1	Transition (2011–2014)	0.0816	0.0640
2	Cup Run (2015–2018)	0.0766	0.0661
3	Rebuilding (2019–2022)	0.0886	0.0690

Figure 8

Logan Couture Expected Goals - Goals Above Expected

Goals above expected is a metric that demonstrates a player's finishing ability relative to the overall quality of their shot attempts. It can be calculated by summing the difference across all shots of the expected goal value minus the actual outcome (1 for goal, 0 for a miss).

	Era	Couture_GAE	Team_GAE
0	Early Contention (2007-2010)	5.44	-75.56
1	Transition (2011-2014)	-1.03	-115.40
2	Cup Run (2015-2018)	34.74	-21.12
3	Rebuilding (2019-2022)	7.21	-74.66

Figure 9

Logan consistently exceeded the expected goal totals across almost all team eras. The rest of his team struggled to convert high-quality chances into goals. The GAE tracks the team's overall scoring efficiently. The closer that GAE is to 0, the better the team did at converting their shot quality into goals. Notably, The GAE metric perfectly follows the order in terms of average playoff rankings by era.

Clutch Index

To further evaluate the situational impact of Logan's scoring I developed a clutch goal index (CGI) that quantifies the importance of a player's goals. The CGI assigns higher values to go-ahead and game-tying goals, especially when scored in the third period or during playoff games. These goals were weighted more heavily in order to reflect their influence on the outcome of games. Insurance goals and blowout scoring were excluded to focus solely on critical moments.

	era	Couture_CGI	team_avg_CGI
0	Cup Run (2015-2018)	1.720930	1.520052
1	Early Contention (2007-2010)	1.791667	1.476210
2	Rebuilding (2019-2022)	1.397590	1.431451
3	Transition (2011-2014)	1.532110	1.614249

Figure 10

Couture's CGI is consistently comparable to the team average, and in the first two eras he significantly outperformed his teammates. These results reinforce Couture's role as a timely scorer during the Shark's most competitive year. In the rebuilding era and transition era, Couture's CGI slightly trails the team average. This denotes a more distributed clutch scoring contribution during these two eras.

Cold Finish Rating

To measure the difficulty of the goals that Logan Couture scored, I developed a metric called the cold finishing rating (CFR). The CFR is defined as the average expected goal value of a player's actual goals. In clearer terms, it denotes how likely each of his scored shots was to become a goal. A lower CFR indicates that a player regularly finishes from low-probability shooting positions. This metric focuses not on volume or total performance like GAE, but on the difficulty of execution for goals actually scored.

	era	Couture_CFR	Team_CFR
0	Cup Run (2015-2018)	0.227640	0.204697
1	Early Contention (2007-2010)	0.210197	0.217908
2	Rebuilding (2019-2022)	0.229948	0.191131
3	Transition (2011-2014)	0.257776	0.216398

Figure 11

Across almost all eras, Couture's CFR remains higher than the team's average. This means that his goals typically came from more favorable positions (higher expected goal opportunities). His highest CFR occurred during the Transition era where his goals had an average expected goal value of 0.258, compared to the team's 0.216. Couture was a sharpshooter that capitalized on positioning and consistently found high-quality scoring opportunities.

Smart Playmaker Metric

To evaluate the effectiveness of how Logan Couture capitalized on chaotic/transitional moments, I created the Smart Playmaker Metric (SPM). This metric calculates the proportion of a player's goals that occurred immediately following a rebound, rush, or turnover. Goals were flagged as chaotic if they came from a rebound, a rush play, or directly followed a giveaway or takeaway. These events represent broken plays or defensive breakdowns where intelligent positioning combined with quick decision making can yield scoring opportunities. A higher SPM indicates a player's ability to exploit disorder on the ice and react under dynamic conditions.

	era	Couture_SPM	team_avg_SPM
0	Cup Run (2015-2018)	0.317829	0.397442
1	Early Contention (2007-2010)	0.375000	0.298895
2	Rebuilding (2019-2022)	0.349398	0.320921
3	Transition (2011-2014)	0.440367	0.423906

Figure 12

Couture's SPM was higher than the teams in all eras except for the Cup Run. This suggests that during the team's most structured years, Couture leaned more on set plays and sustained offense rather than reactive situations. As Couture aged as a player he became smarter and better capitalized on scoring opportunities during these chaotic and reactive situations. During the early contention era, Couture's SPM was vastly greater than his teams demonstrating his ability to apply his experience to remain calm in chaotic situations.

Late Game Hero Rating

The Late Game Hero Rate (LGHR) measures the proportion of a player's goals that are scored during the final moments of a game (within the final five minutes of the third period or during overtime). By isolating goals in this timeframe the LGHR helps evaluate a player's ability to deliver when time is running out, independent of game state. It complements the clutch goal index by emphasizing the timing of goals rather than their impact on the score differential.

	era	Couture_LGHR	team_avg_LGHR
0	Cup Run (2015-2018)	0.178295	0.151545
1	Early Contention (2007-2010)	0.187500	0.150525
2	Rebuilding (2019-2022)	0.277108	0.150573
3	Transition (2011-2014)	0.128440	0.120214

Figure 13

Logan consistently recorded a higher LGHR than his teammates across every single era. During the rebuilding era his LGHR spiked to 27.7% which is nearly doube the team average. Even as the team declined, he remained a key factor in winning late in games. The metric supports the narrative of Couture as a dependable closer and a clutch player.

Conclusion

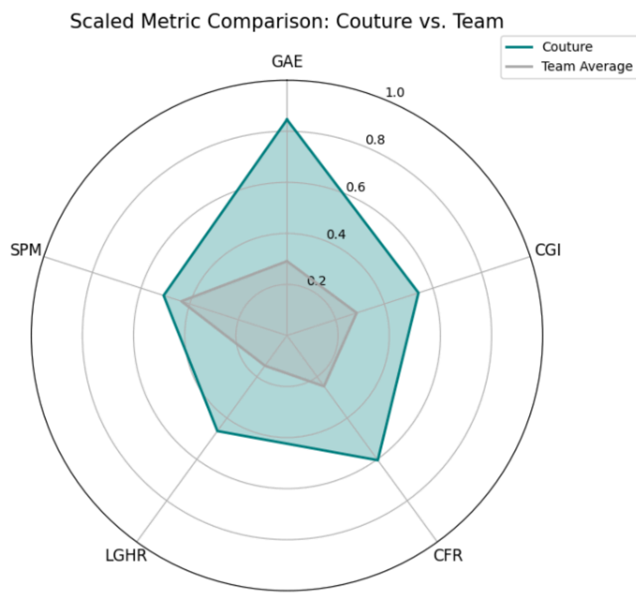

Figure 14

Figure 14 reveals Couture's uniquely well rounded excellence across all the scoring metrics I created. Through timely goals (CGI, LGHR), his finishing ability (CFR), opportunistic awareness (SPM), or outperforming his own expectations (GAE), Couture finds himself out placing the team average. Couture once said he hoped to be "... remembered as a player who worked extremely hard. Someone who would do anything to win, scoring, and blocking shots." This analysis shows he was much more than that. Not only was Couture a hard worker, he was a dominant force whose impact helped shape the very identity of the Sharks throughout their modern era. As the sharks move forward, they will do so without the presence of the player who helped define their identity.