EVALUATING PLAYER IMPACT THROUGH KAST PERCENT AND THE DISTRIBUTION OF IMPACT ACROSS A TEAM USING THE IMPACT DISTRIBUTION COEFFICIENT USING DATA FROM THE EMEA LAST CHANCE QUALIFIER

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KAST is a commonly used measure of impact in tactical FPS games. Using KAST, I have calculated the Impact Distribution Coefficient (IDC), which is a version of the Gini coefficient from Economics (using impact KAST percent instead of income). I hypothesise that the IDC will be negatively correlated with the success of a team (measured by a team's round win percentage). I calculated KAST across the whole tournament for every player, as well as their average KAST percent in winning and losing games. This was done by manually looking through all 736 rounds played. I used this data to calculate each team's tournament IDC as well as IDC of average KAST percent from both wins and losses. The 3 KAST percentages and 3 IDCs were calculated for every player and every team respectively (apart from 2 for Anubis). A significant negative correlation was found between team tournament IDC and round win rate [Pearson's correlation = -0.7233]. From this, we can say that a wider team impact leads to overall greater success on the round level. The implications of these results suggest that teams should prefer players that are more consistent and can provide more stable impact across a whole game, as opposed to "flashy" players that can provide lots of impact in one round and zero in another. With help from Riot's API, both KAST and IDC could see wider use to track teams and players across longer periods of time to help further understand player impact and the distribution of this impact across a team.

2. Introduction

2.1 The Problem of Evaluating Impact

Measuring player impact across any esport is crucial to understanding many key things such as form or fit for a team. VALORANT provides a unique challenge in that the statistics given by the game itself are not ideal for evaluating impact. The game statistics regularly studied are average combat score (ACS), kills, deaths, assists, the difference between kills and deaths, average damage per round (ADR), headshot percent, first kills, first deaths, and the difference between first kills and first deaths. These stats are useful in their own rights for evaluating separate parts of the game, but I would suggest none of these stats are built to evenly reflect a level of contribution at the most basic level.

For example, ACS is the most commonly used statistic for player performance. Riot calculate combat score as follows:

DAMAGE: 1 point each
KILLS based on enemies alive: 150/130/110/90/70
MULTIKILLS: +50 per additional kill
NON-DAMAGING ASSISTS: 25

Because of their role, the main duellist and/or entry player is often purposefully put into a position to obtain first blood as well as receiving the help of support utility to get multi kills (e.g., “flash and dash” etc). Therefore, it is expected and even encouraged for some players to get a higher ACS than others. This means that comparison between players only using ACS is often pointless. For example, the support player on a team may have performed their role perfectly, helping all players of their team to get kills, but the main duellist could still get a higher ACS even when having a worse day simply because they got enough first bloods and multi-kills. ACS definitely has its place, but I think when evaluating a player’s impact, no current stats are useful and we must look elsewhere.

2.2 What is KAST?

Now this is where I think KAST can help. KAST is a measure of impact I first saw used in CSGO. Those of you familiar with the game will have heard of KAST, it factors into HLTV’s “RATING 2.0”, an all-encompassing score designed to rank all players. KAST is an acronym which stands for Kills, Assists, Survived, and Traded. It is expressed as a percentage. For example, a 75% KAST score means that in 75% of all rounds they played, the player got a kill, an assist (of any kind), they survived, or were traded out by a teammate.

I would suggest that this can function better as a measure of impact across a team than current statistics used because it is designed to be equal. Teams may expect varying levels of ACS, but every team’s goal would be to have every player having a KAST rating of 100% and be contributing in some way to every round. For example, a Cypher anchoring C site on Haven may never see an enemy if the opponents end on A, but their presence on the C site still provides impact to the round as the opponents can't simply double back. This is recognised by KAST but not by ACS.

KAST itself is a binary variable, as in the player either did or did not have impact. There is no reflection of the amount or severity of impact a player provides. A 1v5 ace clutch is recorded exactly the same as saving a gun. For this reason, it is important say that KAST is a measure of the floor of impact and does show the extent of impact within a round. Players should not be assessed exclusively using this statistic (or any singular statistic for that matter). It is best used alongside other measures of performance for a more rounded picture of a player. It is also important to note that KAST only reflects on the server impact. An IGL might die but provide a perfect read and call that wins their team a round, and this is not reflected here. Stats like this can provide fantastic insight but it is important to give them all context.

2.3 What is the Impact Distribution Coefficient?

The next key stat I use in this report is something I have named the Impact Distribution Coefficient (IDC). This is a new stat I'm providing and one I have not seen used in VALORANT or other esports. The IDC is a modified version of a statistic that I have experience with from my background in economics. It is a modified version of the Gini Coefficient. The Gini Coefficient is a widely used measure of income inequality within an economy. It ranges from 0 to 1 and if a small percentage of the population have a disproportionally large percentage of an economies income it is larger, and it is closer to 0 if there is a more even distribution. This means that 0 would represent perfect equality and 1 would represent absolute inequality.

While it is most commonly applied to income distribution, at its core it is a simple measure of inequality. In this case, instead of looking at the distribution of income, I have used it to examine the distribution of impact across a team. Impact will be measured by the KAST percentages of players within a team, so the IDC will reflect the evenness of the distribution of the total KAST percentages for a team.

Converting the context like this also means we have to interpret the statistic slightly differently. Instead of IDC ranging from 0 to 1, IDC theoretically caps itself at 0.8. This would be the case where one player had a 100% KAST rating and the rest of the team have 0%. It is also worth noting that this is an extreme point and unlike global economies where the distribution of income can vary widely due to many political reasons, the distribution of impact is likely to be very equal amongst a team. This means we would expect values much closer to 0 and it will be small variations between teams that are important.

I decided to rename this number from the Gini coefficient to the Impact distribution Coefficient as it makes it easier to understand in this context and avoids the connotations that the Gini coefficient has with income distribution.

2.4 IDC vs Round Win Percentage Hypothesis

I think that it is both important and interesting to show the KAST percentages of players throughout the event as well as teams IDC, but I also want to suggest that IDC is relevant to the success of teams. My hypothesis is that teams with lower IDC's will be more successful. Through my own personal experience working with teams as an analyst I have seen time and time again the importance of having 5 players able to perform their job well and most importantly, consistently. I feel that having inconsistent players or too much reliance on a "star" player will ultimately hold a team back. My aim is to investigate whether a more even distribution of impact across a team will lead to a higher percentage of total rounds won. I will also try to show the effectiveness of KAST by examining how often a team with more players having impact than their opponents, wins the round.

3. Methods

3.1 Calculating KAST

Fortunately, KAST is a relatively simple statistic to calculate. I calculated KAST by going through each round of every match played at the EMEA LCQ and examining whether each player got a kill, assist, survived the round, or got traded out. All the rounds were examined using a mixture of VOD reviews and runitback.gg's 2D replay system (I'm not officially endorsed by them but runitback.gg is fantastic for all VALORANT statistics and worth looking into if it is something that interests you). I examined 736 rounds across 35 maps to calculate the KAST percent for each player. For all players, 3 KAST percentages were recorded – these were: Tournament KAST percent, average KAST percent on win and average KAST percent on loss.

Tournament KAST percent is the primary number for each player. It reflects round-based impact across all their rounds played and was calculated using the formula:

$$K = \frac{k}{N}$$

Where K is the final KAST percentage, k is the total number of KAST rounds (rounds where the player has impact) and N is the total number of rounds played in the tournament.

Average KAST percent on win is designed to be a reflection of the average impact a player provided in maps that the team won. This was calculated by the formula:

$$\frac{\sum(K^{W1} + K^{W2} + \cdots + K^{Wn^W})}{n^W}$$

Where n^W is the total number of maps won by the player. K^{W1} is the KAST percent of the player from their first map won, K^{W2} is the KAST percent of the player from their second map won, and K^{Wn^W} is the KAST percent of the player from their n^{th} map won.

Finally, average KAST percent on loss is designed reflect the average impact a player provided in maps that the team lost. This was calculated by the formula:

$$\frac{\sum(K^{L1} + K^{L2} + \cdots + K^{Ln^L})}{n^L}$$

Where n^L is the total number of maps lost by the player. K^{L1} is the KAST percent of the player from their first map lost, K^{L2} is the KAST percent of the player from their second map lost, and K^{Ln^L} is the KAST percent of the player from their n^{th} map lost.

3.2 Calculating the Impact Distribution Coefficient

Calculating IDC for each team is more challenging. It can be done using the Lorenz curve. We can show this by plotting the cumulative percentage of a team that a player makes up, against the cumulative percent of impact that each player has. To explain further I will use an example.

You have a standard team of 5 players with their respective KAST scores shown below (These have been made purposefully unrealistic to aid the example).

Table 1: Example KAST Scores

Player	KAST SCORE	% OF IMPACT	% OF TEAM	CUMULATIVE % OF TEAM	CUMULATIVE % OF IMPACT
1	10%	0.05	0.2	0	0
2	20%	0.10	0.2	0.2	0.05
3	30%	0.15	0.2	0.4	0.1
4	40%	0.20	0.2	0.6	0.3
5	100%	0.50	0.2	0.8	0.55
				1	1

We then know that each player makes up 20% of the total team each and we can see the percent of impact each player holds. These are then both added cumulatively, as shown in the 2 columns furthest right, and are plotted against each other. We will get one perfectly diagonal line known as the line of equality, and another line underneath that is known as the Lorenz curve.

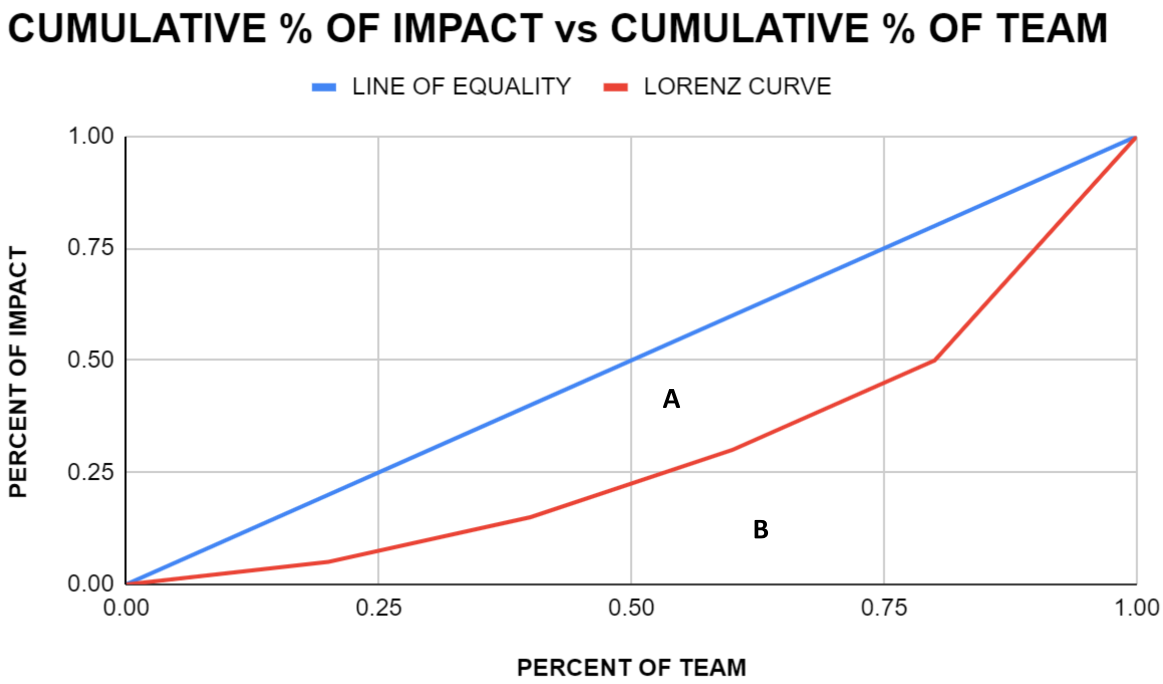

Figure 1: Example Lorenz curve

Figure 1 shows these two lines plotted against each other. The blue line represents the line of equality and the red line represents our Lorenz curve. To calculate the IDC, we then need to know the size of both area's A and B. Typically, you would focus on area B as it is the same as calculating the area under any other curve. This can be done by any method you see fit such as integration, but I used the most simplified version and that's turning the results into bars and summing up the area. I will demonstrate how I did this below.

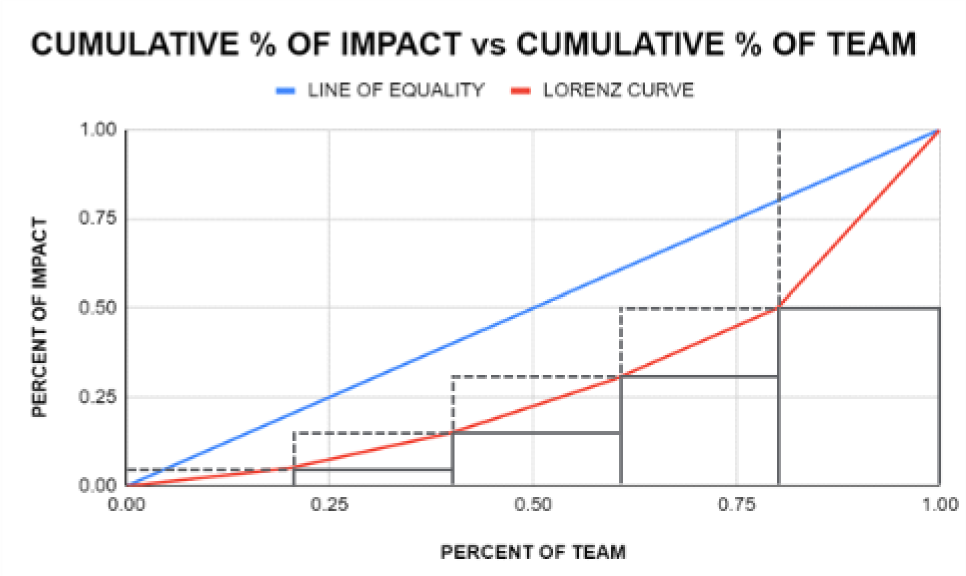

Figure 2: Example Lorenz curve with bars

Figure 2 shows the same curves as figure 1, with the demonstrative bars drawn on. We can see here that we have 5 pieces of data and the Lorenz curve is made up of 5 separate line segments. When calculating the area underneath the curve there are 2 options. You can either use the higher bars shown by the dashed grey lines or the lower bars shown by the solid grey lines. The problems with these methods are that taking the dotted lines will give us an underestimation of area A and using the solid lines will give us an overestimate of area A. To avoid this bias, we take the average of the lower-bound and the higher-bound of each bar and the sum of these bars will perfectly give us area B.

Table 2: Example cumulative percentages and Lorenz curve area

CUMULATIVE % OF TEAM	CUMULATIVE % OF IMPACT	AREA UNDER LORENZ CURVE
0	0	
0.2	0.05	0.005
0.4	0.1	0.015
0.6	0.3	0.04
0.8	0.55	0.085
1	1	0.155

Here we can see these averages calculated with our example. So, the calculate the area of the first bar we would calculate as follows

$$0.2\left(\frac{0+0.05}{2}\right) = 0.005$$

This continues all the way along for all 5 bars. Once this is done, we can sum together the area of all bars to get the area B. In this example, area B = 0.3. Next, we calculate area A as follows

$$A = 0.5 - B$$

This gives us A = 0.2. Finally, we apply the last calculation to give us our final IDC.

$$IDC = \frac{A}{A+B}$$

For our example, this would result in:

$$IDC = \frac{0.2}{0.2+0.3} = 0.4$$

This process was applied for every team using players tournament KAST percent, average KAST percent on win and average KAST percent on loss. This provided me with 3 IDC results for every team (but only 2 for Anubis as they had no winning maps).

3.3 Calculating Round Win Percentage

In order to assess whether a team's IDC had an effect on the success of a team, I needed to determine a dependent variable to show this success. I decided to use a team's round win percentage as it provides us with enough variation and sample size, as well as being directly linked to the success of a team. To calculate this, I used the following:

$$\frac{n^W}{N}$$

Where n^W is the number of rounds a team won and N is the total amount of rounds a team played. This number was compared to the team's tournament IDC and a correlation coefficient was calculated.

3.4 Calculating the Greater Impact Win Percentage

The final statistic calculated was the greater impact win percentage. This statistic is designed to show how often a team that has more players providing impact to the round than their opponents, wins the round. I discounted rounds where both teams had the same number of players contributing for this calculation. I used the following formula:

$$\frac{G}{G+S}$$

Where G is the amount of rounds the team with the greater number of players having an impact won the round, and S is the amount of rounds the team with the smaller number of players having an impact on the round, won the round.

4. Results

4.1 Tournament KAST Percentages

Calculating the player's tournament KAST percentages was one of the main drives for this study and allows us to see how much impact each player had on a round to round basis across the tournament.

Table 3: Tournament KAST percentages

PLAYER	TEAM	KAST ROUNDS	TOTAL ROUNDS	KAST %	RANK
Jamppi	Liquid	174	220	79.09%	1
Brave	SMB	143	188	76.06%	2
Turko	SMB	142	188	75.53%	3
Nivera	Liquid	166	220	75.45%	4
L1NK	Liquid	166	220	75.45%	5
ScreaM	Liquid	165	220	75.00%	6
Leo	Guild	239	321	74.45%	7
AvovA	G2	168	228	73.68%	8

soulcas	Liquid	160	220	72.73%	9
nukkye	G2	164	228	71.93%	10
koldamenta	G2	164	228	71.93%	11
qRaxs	Futbolist	151	211	71.56%	12
MOJJ	Futbolist	151	211	71.56%	13
qw1	Futbolist	150	211	71.09%	14
russ	SMB	132	188	70.21%	15
Izzy	SMB	132	188	70.21%	16
Sasuke	Futbolist	147	211	69.67%	17
glovee	Oxygen	89	129	68.99%	18
Avez	Anubis	57	83	68.67%	19
draken	Guild	220	321	68.54%	20
Sayf	Guild	219	321	68.22%	21
Yacine	Guild	217	321	67.60%	22
Paura	SMB	127	188	67.55%	23
m1tez	Oxygen	87	129	67.44%	24
STERBEN	Futbolist	142	211	67.30%	25
bonkar	Guild	216	321	67.29%	26
XiSTOU	Oxygen	86	129	66.67%	27
Toronto	Oxygen	85	129	65.89%	28
zeddy	OBG	60	92	65.22%	29
Shalaby	Anubis	53	83	63.86%	30
Mixwell	G2	144	228	63.16%	31
keloqz	G2	143	228	62.72%	32
Unity	Oxygen	80	129	62.02%	33
chrollo	Anubis	50	83	60.24%	34
fr0st	Anubis	50	83	60.24%	35
Minse	OBG	55	92	59.78%	36
Coffee	OBG	55	92	59.78%	37
Sp1ke	OBG	53	92	57.61%	38
zizox	Anubis	37	66	56.06%	39
hugeon	OBG	48	92	52.17%	40
Tuna	Anubis	8	17	47.06%	41

Table 3 offers some interesting observations. Firstly, you can see how see how all 5 Team Liquid players make it into the top 10 for the tournament. This continues as players from the better performing teams land in the upper half of the table and the worse performing teams are more commonly towards the bottom half of the table. We also see a wide range of KAST percentages showing that having “impact” in a round is often not as easy as it may sound when explaining the statistic.

4.2 Average KAST Percentages on Win and Loss

Now we can examine a player’s average KAST score on both winning matches and losing matches. This is important as it helps see when different players perform best, as well as eliminating the winning bias that is present in Table 3.

Table 4: Average KAST percent on win

PLAYER	TEAM	AVG KAST WIN	RANKING
Brave	SMB	83.83%	1
russ	SMB	81.17%	2
glovee	Oxygen	81.01%	3
Jamppi	Liquid	80.90%	4
Turko	SMB	80.38%	5
Leo	Guild	80.34%	6
m1tez	Oxygen	80.29%	7
qRaxs	Futbolist	80.25%	8
Izzy	SMB	79.46%	9
nukkye	G2	79.11%	10
AvovA	G2	78.74%	11
zeddy	OBG	78.26%	12
Coffee	OBG	78.26%	13
ScreaM	Liquid	78.10%	14
Nivera	Liquid	77.81%	15
Toronto	Oxygen	77.64%	16
L1NK	Liquid	77.61%	17
MOJJ	Futbolist	77.49%	18
soulcas	Liquid	77.43%	19
Sayf	Guild	77.37%	20
Yacine	Guild	75.69%	21
Unity	Oxygen	75.24%	22

draken	Guild	74.95%	23
qw1	Futbolist	74.11%	24
STERBEN	Futbolist	74.07%	25
hugeon	OBG	73.91%	26
Paura	SMB	72.76%	27
Sasuke	Futbolist	72.73%	28
koldamenta	G2	72.29%	29
bonkar	Guild	71.94%	30
XiSTOU	Oxygen	71.39%	31
Mixwell	G2	70.59%	32
Sp1ke	OBG	69.57%	33
Minse	OBG	69.57%	34
keloqz	G2	65.42%	35
chrollo	Anubis		36
zizox	Anubis		36
Avez	Anubis		36
Tuna	Anubis		36
Shalaby	Anubis		36
fr0st	Anubis		36

Table 5: Average KAST percent on loss

PLAYER	TEAM	AVG KAST LOSS	RANKING
koldamenta	G2	72.71%	1
Turko	SMB	72.59%	2
Brave	SMB	70.04%	3
AvovA	G2	69.29%	4
Avez	Anubis	67.94%	5
Jamppi	Liquid	67.46%	6
Nivera	Liquid	66.67%	7
XiSTOU	Oxygen	65.40%	8
nukkye	G2	65.40%	9
qw1	Futbolist	65.31%	10
L1NK	Liquid	65.08%	11
Leo	Guild	64.99%	12
Paura	SMB	64.46%	13

qRaxs	Futbolist	64.40%	14
ScreaM	Liquid	63.89%	15
Izzy	SMB	63.78%	16
russ	SMB	63.17%	17
Shalaby	Anubis	62.99%	18
glovee	Oxygen	62.94%	19
Toronto	Oxygen	62.26%	20
Sayf	Guild	62.16%	21
m1tez	Oxygen	61.90%	22
Sasuke	Futbolist	61.82%	23
MOJJ	Futbolist	61.53%	24
keloqz	G2	60.44%	25
bonkar	Guild	60.31%	26
zeddy	OBG	59.80%	27
draken	Guild	59.53%	28
fr0st	Anubis	58.58%	29
chrollo	Anubis	58.41%	30
Yacine	Guild	58.13%	31
STERBEN	Futbolist	57.97%	32
Unity	Oxygen	55.59%	33
Minse	OBG	54.94%	34
zizox	Anubis	53.85%	35
Mixwell	G2	53.63%	36
Sp1ke	OBG	53.41%	37
soulcas	Liquid	53.17%	38
Coffee	OBG	51.73%	39
Tuna	Anubis	47.06%	40
hugeon	OBG	43.59%	41

Anubis have no values here because they did not win a map.

Tables 4 and 5 are interesting as in both, the top performing players are not necessarily at the top of the table, and the worse performing players this tournament are not necessarily at the bottom.

Every player had a higher average KAST percent on win than on loss apart from G2’s koldamenta who was on average **0.42** percentage points better in losing games.

We can also compare the difference of the two results for a player and we find that players on average have a higher average KAST percent in wins than losses by **14.58** percentage points with a standard deviation of **5.56** percentage points

4.3 Greater Impact Win Percentage

Next, we will examine the results for the greater impact win percentage. Out of a total **736** rounds, one team had more players providing impact than the other in **663** rounds. Out of these **663** uneven rounds, the team had more players providing impact won **622** times giving us a final greater impact win percentage of **93.82%**.

This is a very high percentage showing us that more players having impact in a round is certainly beneficial.

4.4 Tournament IDC

The tournament IDC is the next key statistic we will examine as this is the main way of assessing the impact distribution of players across their teams within the tournament.

Table 6: Tournament IDC

TEAM	TOURNAMENT IDC	RANKING
Futbolist	0.01187584345	1
Liquid	0.01395908544	2
Guild	0.01764176418	3
Oxygen	0.018735363	4
SMB	0.02485207101	5
G2	0.03575989783	6
OBG	0.03837638376	7
Anubis	0.06152401169	8

These values are very small (as expected) and are all less than 0.1. If these were economies and we were examining these numbers for income distribution, we would say that they are all incredibly near perfectly equal. Of course, these are not economies and the context means that the small differences between these, actually means a lot in terms of the distribution of impact. We see the teams ranked here with the smallest IDC, meaning most equal team, in first place, with the 8th ranked team being the most unequal.

4.5 IDC From Average KAST Percentages on Win and Loss

Similarly, we can see how equal the impact was for each team when using the data from average KAST percentages on wins and losses.

Table 7: IDC's calculated using average KAST percentages on win

TEAM	IDC FROM AVG WIN KAST %	RANKING
Liquid	0.007597617638	1
Futbolist	0.01951534791	2
Guild	0.0202138881	3
SMB	0.02399461562	4
Oxygen	0.02518703242	5
OBG	0.02823529412	6
G2	0.03880888175	7
Anubis		8

Table 8: IDC's calculated using average KAST percentages on loss

TEAM	IDC FROM AVG LOSS KAST %	RANKING
Guild	0.02142631179	1
Futbolist	0.02256907791	2
Oxygen	0.02684177135	3
SMB	0.03006851839	4
Liquid	0.03964868256	5
OBG	0.05410745553	6
G2	0.05851113075	7
Anubis	0.06306323529	8

Once again there are interesting results to be drawn from the comparison of these two tables. We saw every teams IDC increase going from winning data to losing data, meaning that every team was on average more unequal in the distribution of impact in losses than in wins. There was an average difference of **0.1280** between wins and losses.

4.6 Round Win Percentage and the Correlation Between Round Win Percentage and Tournament IDC

In order to help us confirm the hypothesis that a more even distribution of impact leads to more success, we needed to calculate the round win percentage for every team. The results are shown in Table 9.

Table 9: Round win percentages

TEAM	ROUNDS WON	TOTAL ROUNDS	WIN %	RANK
Liquid	130	220	59.09%	1
Guild	167	321	52.02%	2
G2	118	228	51.75%	3
SMB	97	188	51.60%	4
Futbolist	102	211	48.34%	5
Oxygen	62	129	48.06%	6
Anubis	30	83	36.14%	7
OBG	30	92	32.61%	8

Here we can see round win percentages for every team. As expected, the teams that performed better at the tournament in general have a higher round win percentage than worse performing teams.

The key to solving the hypothesis is comparing this round win percentage to the results from section 4.4, tournament IDC

Table 10: Tournament IDC and round win percentage

TEAM	IDC	WIN %
G2	0.03575989783	51.75%
Anubis	0.06152401169	36.14%
Futbolist	0.01187584345	48.34%
Oxygen	0.018735363	48.06%
SMB	0.02485207101	51.60%
Guild	0.01764176418	52.02%
Liquid	0.01395908544	59.09%
OBG	0.03837638376	32.61%

Now that we have both the variable for impact distribution, the IDC, our variable for success and round win percentage, we can examine the correlation between the 2 datasets to see if there is a correlation.

When we calculate the Pearson Correlation Coefficient for these two datasets, we get a coefficient of **-0.7233**, suggesting a strong negative correlation between the two variables. This means that, as tournament IDC increases, round win percentage decreases.

Through the use of hypothesis testing, I was able to confirm that this correlation coefficient is statistically significant at the 5% level.

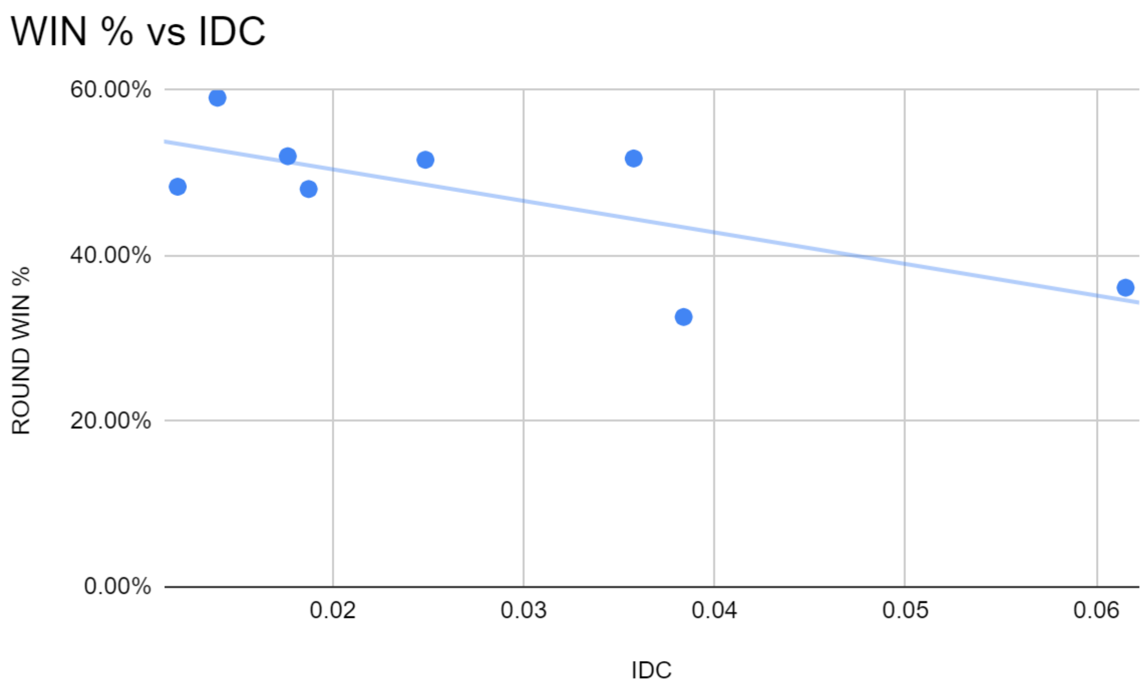

Figure 3: Round win percent vs IDC scatter graph

Figure 3 demonstrates the relationship between round win percentage and IDC. We can see how the data fits around the trend line, and due to the statistical significance of the data, this line can be used for prediction. For example, if a team had an IDC of 0.05, we could predict a round win percentage of just under 40%.

5. Discussion

5.1 Understanding the Results

From our results there are some clear conclusions that can be drawn. First and foremost, there is a statistically significant relationship between a team's tournament IDC and their round win percentage. This relationship is also supported by evidence from the other calculated statistics, namely the fact that a team with wider impact than their opponents won the round over 90% of the time, and the fact that every team's IDC was higher using data from their losing matches than their winning matches. The core statistically significant relationship and the supporting statistics mean that we are able to confirm the original hypothesis, that teams with more even distributions of impact will on average perform better on a round to round basis. Even though I have not been directly able to prove exact causation, the correlation is certainly important.

5.2 Implications

The implications of these findings are applicable in many areas of VALORANT. I will focus on the professional level of VALORANT here as the results mean much more in that context than something like solo queue ranked for example. The results suggest that when assembling teams, consistency is an incredibly important factor of being a good player. In fact, it advocates for the benefits of consistency over star potential. When making a choice between two players, the results of this paper would suggest favouring more steady, consistent players over players with large variation in their play with lots of impact in some rounds and no impact in others.

Furthermore, the results highlight the idea of “survival” having a positive impact on a round for your team. This makes sense theoretically but is commonly not applied on the server. In a winning round, a players existence has impact without anything else as they are helping control the map. If the opposing team has more players alive than you, you have to assume that they can control more space and this makes deciding where to execute trickier, as well as where to defend.

Surviving also brings value in losing rounds as it will mean saving a weapon to help keep your economy strong. This idea of saving weapons is often overlooked and typically we see players go for it in situations where they are statistically very unlikely to succeed. The results of this study show that it is important to know when to save your weapon and the impact that this will bring to your team . Ultimately, this will be more beneficial for the team in the long run.

5.3 Limitations

There are a few limitations of this study that should be highlighted. Firstly, as briefly mentioned before, KAST doesn’t tell the full story of a player’s impact in a round. All off-server impact is not included. This includes IGL’ing and calls being made primarily, but also moral effects and other mental boosts. This means a player could have a definitive impact on the round whilst KAST would not count the player as having impact.

Secondly, the sample size is small as only 8 teams were included. This is an issue as more data on player’s KAST percent and their teams corresponding IDC can help create a more accurate trend line and strengthen the hypothesis. The problems with this include the time-consuming data collection to calculate KAST percent, in addition to the time taken to make the appropriate calculations. This small sample size is also limited by the fact that all the teams studied are from the same region, there could be an unobserved bias due to this.

Additionally, the data being studied is only from one LAN tournament. There are a lot of unobserved variables at play here that could impact both a player’s impact and the teams round win percentage. For more accurate results, each team should be tracked for a longer period of time in order to obtain more accurate values for both IDC and round win percentage.

5.4 Conclusions

My aim for this study was to provide fresh statistics for use in VALORANT by calculating KAST percent for every player and an IDC for every team. I hope that I have proven the value of both of these statistics. Going forward, if the time to calculate KAST can be reduced, through the use of Riots API by people who understand it, I see no reason why both KAST and IDC couldn't be implemented for wider use to track players and teams across every game they played.

I while I hope my work has been useful on a top level, I also hope that individuals can also use my research such as coaches or analysts adding KAST and IDC into their own stat tracking. Finally, I hope I have provided a case for the usefulness of the stats as well as the tools needed for these statistics to be implemented by both teams and other companies involved in VALORANT esports.

6. Figures and Tables

6.1 List of Figures

6.2 List of Tables