Complexity Analysis in Counter Strike 2 Spray Patterns

Cauan Santos[1], **Rodolfo Garcia**[1]

[1]Departamento de Computação (DCOMP) – Universidade Federal de Sergipe (UFS)
São Cristóvão – SE – Brasil

{cauan.silva,rodolfo.botto}@dcomp.ufs.br

Abstract. Introduction*: The Counter-Strike (CS) franchise has shown benefits for players social development and for the stimulation of motor and cognitive skills, establishing relationships between improvements in physical, mental health and in-game performance. Individual skills of a CS2 player, such as aiming and control over weapon spray patterns, are extremely important for maximizing performance metrics.* ***Objective:*** *this work aims to analyze the complexity of Counter-Strike 2 spray patterns, and then compare it with the cost of each weapon in the game. Additionally, this work also analyzes the length of sprays performed by professional players as a way of showing how difficult is to control the recoil compensation in CS2.* ***Methodology or Steps****: The complexity of spray patterns in Counter-Strike 2 was computed using the Lempel-Ziv (LZ) method, adapted to problems in which the data can be represented as time series. In this work, spray patterns are treated as temporal sequences of movement, allowing their complexity to be calculated based on the number of new patterns found throughout the sequence.* ***Results:*** *Within the set of normalized LZ complexities, rifle weapons appear among the highest complexities, but do not represent the most expensive weapon. This indicates that these weapons present greater structural irregularity in the adopted symbolic representation. In contrast, SMGs and machine guns appear as weapons with less complex spray patterns. Lastly, professional players' spray lengths are considerably smaller than the magazine capacity of the weapons and usually do not empty the full magazine during a spray, even when using weapons with relatively simple spray patterns.*
Keywords *Spray Pattern Complexity, Lempel-Ziv Method, CS 2, Temporal Data.*

1. Introduction

The popularization and financial success achieved by the Counter-Strike (CS) franchise have been prominent in the gaming market and the global economy for several decades [Marshall et al. 2022], [Kulkarni e Kuber 2026]. To become a professional, a good CS player depends on several individual and collective factors, since a professional team is composed of a coach and five players who define and execute strategies. Regarding the individual skills of a player, aiming and mastering weapons are extremely important for maximizing the performance metrics listed by [Kulmakorpi 2025]: damage, hits and accuracy.

Mastering a weapon depends on a good control over it spray pattern, skill addressed in this work. A spray pattern describes the trajectory of the bullets when a weapon is fired continuously. Since each weapon has a unique spray pattern with its own specific magazine capacity and complexity, understanding the pattern and a good recoil compensation, which is the movement of mouse to maintain the bullets in the target, are essential for effective weapon control.

This work aims to analyze the complexity of Counter-Strike 2 spray patterns using an adapted Lempel-Ziv method. The complexity assessment is given in two ways: 1) visually, by comparing a simple spray pattern with a complex one, and 2) through the professional players mastery of spray patterns, by measuring the length of sprays performed as a way of showing how difficult is to control the recoil compensation in CS2.

Despite the complexity, the factors that most influence the choice of a weapon in a round are its cost and the base damage. According to [Marshall et al. 2022], more expensive weapons increase a player's chances of not being eliminated during rounds. This conclusion raises the following research question: do more expensive weapons, which are more powerful, are associated with the complexity of their sprays?

In addition to the potential financial return for professional players, recent scientific studies have explored its benefits for players social development and for the stimulation of motor and cognitive skills, establishing relationships between improvements in physical, mental health and in-game performance [Kulmakorpi 2025], [Wright et al. 2002], [Kulkarni e Kuber 2026]. Following balanced training programs without excessive duration, in order to develop specific skills to become a good CS player can also have a positive influence on health. Thus, this work also aims to help amateurs to choose weapons that can be easily mastered and, above all, helping to increase level and to keep the game fun.

The remainder of this paper is organized as follows: Section 2 presents related works, Section 3 provides the theoretical background behind the computation of spray complexity using the Lempel-Ziv method, Section 4 describes the experiments for complexity analysis which results are in Section 5 and, finally, Section 6 presents the conclusions and proposals for future works.

2. Related Work

This section lists related works on performance analysis in Counter-Strike 2. Most commonly, telemetry data from the dynamic scenario of matches have been used to measure the probability of a given player being eliminated during rounds, as well as to predict round outcomes [Marshall et al. 2022], [Xia et al. 2025].

In [Kulmakorpi 2025], the purpose is to investigate the relationship between different physical warm-ups and the aiming performance of Counter-Strike 2 and Valorant players. Performance is measured using damage, hits, and accuracy percentage, and the authors conclude that reaction warm-ups are the most effective, although it is important to identify individualized warm-up routines.

The evolution process of a team depends heavily on the strategies designed by the coach. To prevent these strategies from becoming public during training sessions, studies aimed at creating more intelligent bots are highly relevant. Intelligent bots seek to behave similarly to professional players in order to raise the training level of both professional and amateur teams [Durst et al. 2024].

On the other hand, an excessive pursuit of performance can eliminate the various benefits listed above. Considering unbalanced training programs and long competitive matches, they may also result in physical and cognitive fatigue, as well as stress. In [Kulkarni e Kuber 2026], physiological, cardiac and ocular signals were recorded using sensors and applied machine learning to predict cognitive states and game performance.

3. Lempel-Ziv Method for Temporal Data

The complexity of spray patterns in Counter-Strike 2 was computed using the Lempel-Ziv method [Lempel e Ziv 1976], originally proposed for the analysis of symbolic sequence complexity, and which became widely known for its application in data compression algorithms.

Its central idea is to identify patterns in a sequence of symbols, allowing the degree of complexity of the analyzed data to be measured. The logic of the method is based on the principle that sequences with repetitive patterns have lower complexity, whereas sequences with a greater amount of pattern variation have higher complexity.

In a simplified way, the algorithm scans a sequence of symbols and divides it into segments. Whenever a previously unobserved subsequence appears, it is considered a new entry in a pattern dictionary. At the end of the process, the number of identified segments represents the complexity of the sequence. Thus, a sequence with many repeated subsequences tends to generate fewer segments and, therefore, lower complexity. In contrast, a sequence with greater variation tends to generate more new segments, indicating higher complexity.

The application of Lempel-Ziv in this work is inspired by the approach proposed by [Montalvão e Canuto 2014] for signal comparison and classification. This approach shows that the method can be used in pattern recognition problems, especially when the analyzed data can be represented as temporal sequences. Since the original method operates on symbolic sequences, Montalvão and Canuto explain that continuous temporal numerical signals must be converted into symbolic sequences before applying Lempel-Ziv. This process is performed through quantization, in which continuous signal values are grouped into discrete categories.

In the context of this work, each spray pattern can be represented as a temporal sequence of movement points. Each point p_t in the spray can be described by its coordinates over time:

$$p_t = (x_t, y_t)$$

From two consecutive points between t and $t-1$, the displacement vector Δp_t is computed as:

$$\Delta p_t = (\Delta x_t, \Delta y_t) = (x_t - x_{t-1}, y_t - y_{t-1})$$

Since these displacements are continuous numerical values, they must be converted into symbols before applying Lempel-Ziv. Thus, the spray movement sequence is quantized into a symbolic sequence, in which each symbol represents a discrete characteristic of the movement at that instant.

For example, a simplified sequence of five displacements can be represented as follows:

$$(0.12, -0.35),\ (0.1, -0.30),\ (-0.05, -0.28),\ (-0.20, 0.04),\ (-0.18, 0.10)$$

After quantization, whose variables and symbolic alphabet are detailed in Section 4, this numerical sequence can be converted into the following sequence of five symbols:

$$s_1,\ s_2,\ s_3,\ s_4,\ s_5$$

This symbolic sequence is then used as input for the Lempel-Ziv algorithm. As a result, sprays with low pattern variation tend to be simpler to execute. On the other hand, sprays that require more irregular or less repetitive movements tend to generate a larger number of new symbolic segments, indicating higher complexity.

4. Experiments

This section describes the two experiments conducted in this work to calculate spray patterns complexity. Section 4.1 details how the Lempel-Ziv method defines the complexity of CS2 weapons spray patterns. Here, complexity validation is performed visually by comparing the original shapes of sprays considered simple with a complex one. Section 4.2 details the experiment to measure the length of sprays performed by professional players using several weapons as a way of showing how difficult is to control the recoil compensation in CS2.

4.1. Spray Pattern Complexity

The methodology for this experiment is divided into three steps: data collection, construction of symbolic sequences and complexity calculation using the Lempel-Ziv method applied to temporal data.

4.1.1. Data Collection

The dataset corresponding to the weapons' reference spray patterns was extracted from publicly available GIFs on the Leetify website[1]. Each GIF was processed frame by frame to identify the position of the points in the spray pattern. As a result of this processing, a compensation movement dataset was built, considering that the player must move the crosshair in the opposite direction of the weapon's visual recoil displacement. For the complexity calculation, the information consisted of the weapon identification, the index of the point in the spray pattern, and the horizontal and vertical movement displacements, represented by the variables *weapon*, *shot_idx*, *dYaw*, and *dPitch*, respectively. Thus, the complexity is based solely on the shape of the spray pattern, without taking into account other types of information, such as mouse acceleration.

[1] https://leetify.com/cs2-spray-patterns

Figure 1 shows examples of accumulated compensation trajectories generated from the extracted reference spray patterns for the M4A4, AK-47, and Galil. The green marker indicates the beginning of the sequence, the red marker indicates the end, and the color scale represents the shot index. All sprays captured in the GIF frames were visually validated and compared with the original sprays.

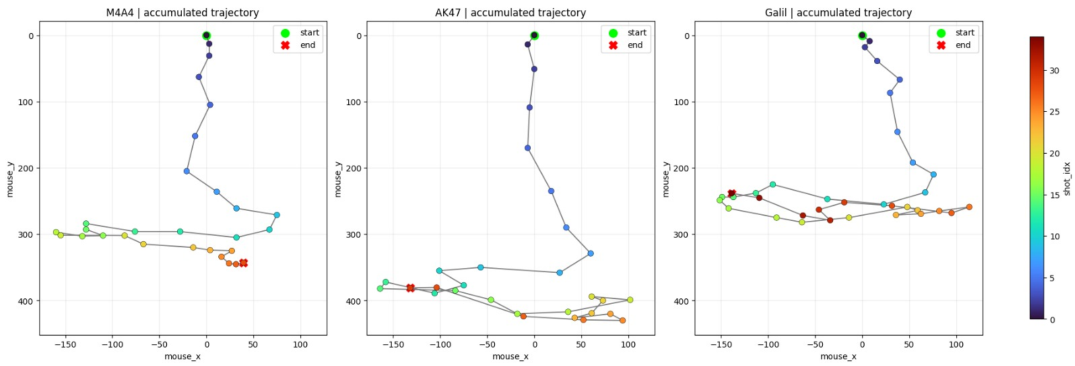

Figura 1. Examples of accumulated compensation trajectories for the M4A4, AK-47, and Galil reference spray patterns.

4.1.2. Construction of Movement Sequences

To calculate the complexity of the spray patterns, the data were grouped by weapon and ordered according to the index of each point in the pattern. The starting point, identified by *shot_idx = 0*, was removed because it represents only the initial position of the spray and not an effective displacement associated with recoil control.

Thus, each spray with n displacement points was represented as an ordered sequence of displacements:

$$S_w = [(dYaw_1, dPitch_1), (dYaw_2, dPitch_2), ..., (dYaw_n, dPitch_n)],$$

where S_w represents the movement sequence of weapon w, and each pair $(dYaw_i, dPitch_i)$ represents the horizontal and vertical displacement associated with a point in the spray pattern.

4.1.3. Conversion to Symbolic Sequence

Since the Lempel-Ziv method operates on symbolic sequences, the displacement pairs $(dYaw, dPitch)$ were converted into symbols. For this purpose, only the sign of each displacement was considered: negative, zero or positive.

The sign function and a pair of signs PF can be represented as:

$$sign(v) = \begin{cases} -1, & \text{if } v < 0 \\ 0, & \text{if } v = 0 \\ 1, & \text{if } v > 0 \end{cases}$$

$$PF = (sign(dYaw), sign(dPitch))$$

Finally, an alphabet of nine possible symbols was used:

PF	$Symbol$
$(-1, 1)$	a
$(0, 1)$	b
$(1, 1)$	c
$(-1, 0)$	d
$(0, 0)$	e
$(1, 0)$	f
$(-1, -1)$	g
$(0, -1)$	h
$(1, -1)$	i

After this process, each spray pattern was represented as a symbolic string. For example, the sequence of displacements used in Section 3 is converted into the sequence $iigaa$. This string preserves the temporal order of a spray pattern and is used as input for the calculation of Lempel-Ziv complexity.

4.1.4. Lempel-Ziv Complexity Calculation

After converting the spray patterns into symbolic sequences, the classical Lempel-Ziv (LZ) method was applied. The algorithm scans the string and identifies new segments that had not previously appeared in the sequence. The total number of segments found represents the raw LZ complexity of the analyzed pattern.

The raw complexity was calculated for all weapons present in the dataset. However, since this measure tends to increase with the length of the sequence or with the number of bullets in a magazine capacity, the normalized version of the complexity was used for comparison, as follows:

$$C_{norm}(s) = \frac{C(s)}{n/\log_{\alpha}(n)},$$

where $C_{norm}(s)$ and $C(s)$ represent, respectively, the normalized and raw LZ complexity of sequence s, n represents the length of the symbolic sequence, and $\alpha = 9$ corresponds to the size of the alphabet used.

4.2. Spray Length Obtained by Professional Players

Here, continuous shooting events, or sprays, were obtained from matches available on HLTV and performed by professional players in the following Counter-Strike 2 tournaments: PGL Cluj-Napoca 2026, IEM Kraków 2026, BLAST Bounty 2026 Season 1 Finals, StarLadder Budapest Major 2025, BLAST Rivals 2025 Season 2, and IEM Chengdu 2025.

After analyzing all obtained events, 12,091 sprays containing at least three consecutive shots were filtered (Table 1). This criterion was adopted to distinguish spray control from isolated shots or very short bursts. The final spray dataset consisted of ten professional players with significant influence in the CS scene: flameZ (1634), ZywOo (1048), XANTARES (1356), donk (1096), FalleN (1028), KSCERATO (1402), YEKINDAR (1194), m0NESY (890), NiKo (1140), and kyousuke (1303).

Tabela 1. Distribution of weapons in the professional players' spray dataset.

Weapon	Number of sprays	Percentage
AK-47	6072	50.22%
M4A1	2979	24.64%
M4A4	855	7.07%
Galil AR	563	4.66%
Glock-18	389	3.22%
MP9	364	3.01%
MAC-10	197	1.63%
Tec-9	167	1.38%
Dual Berettas	166	1.37%
Five-SeveN	129	1.07%
FAMAS	116	0.96%
P250	41	0.34%
MP7	27	0.22%
MP5-SD	11	0.09%
UMP-45	8	0.07%
CZ75 Auto	6	0.05%
SG 553	1	0.01%
Total	12091	100.00%

Each spray event contains the following information: player identification, weapon used, map, round, number of shots fired, and the spray time series. This series is represented by the same variables $dYaw$ and $dPitch$.

This experiment aims to analyze the length of sprays obtained by professional players in order to show how difficult it is to control recoil compensation and master a weapon in CS2.

5. Results

As in the previous section, the results are divided according to the two experiments. Section 5.1 presents the results of the spray pattern complexity analysis using LZ method, while Section 5.2 presents the results regarding the spray length obtained from professional players.

5.1. Spray Pattern Complexity

This experiment was restricted to automatic weapons, since they are more directly associated with the mechanics of continuous spray control. Thus, the following categories were considered: rifles, submachine guns, and machine guns. Figure 2 shows the average normalized LZ complexity by automatic weapon category. The comparison indicates that rifles, including Galil, M4A4, AUG, FAMAS, AK-47, and SG-553, present the highest average normalized LZ complexity among automatic weapons. SMGs, including MP9, MP7, MAC-10, UMP-45, P90, and Bizon, appear next, followed by machine guns, represented by Negev and M249.

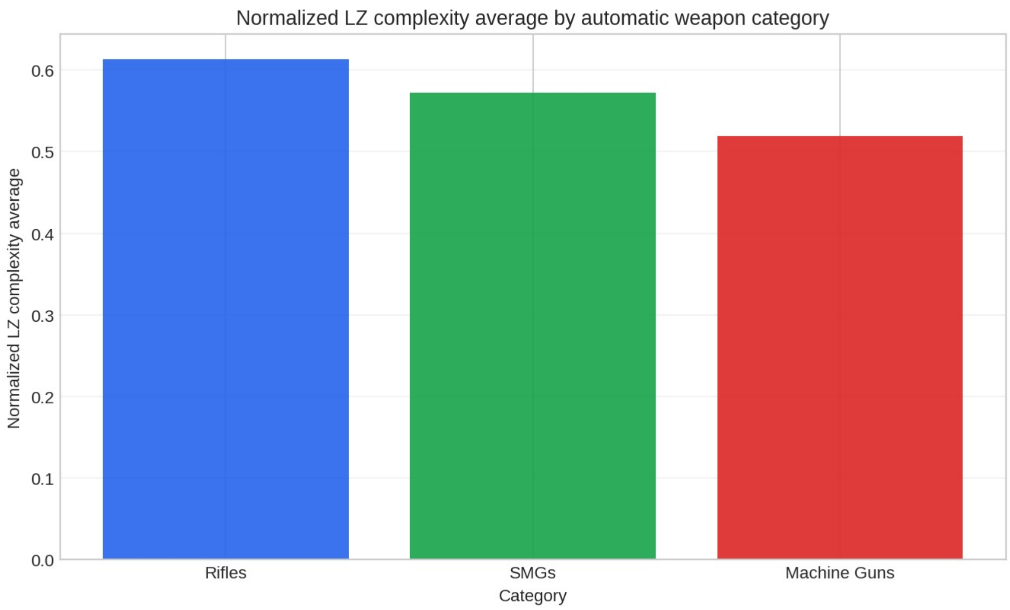

Figura 2. Average normalized LZ complexity by automatic weapon category.

Figure 3 details the normalized complexity for each automatic weapon. As can be observed, Galil, Bizon, and M4A4 present the most complex spray patterns, with very close values. This indicates that these weapons present greater structural irregularity in the adopted symbolic representation. On the other hand, MAC-10 presents the simplest spray pattern, followed by Negev. The complexity obtained by AK-47 is the simplest in rifles category, what can explain the popular use presented in Table 1.

Due to space constraints, the images will not be included here, but the listed observations can easily be viewed on the Leetify website. The first 10 bullets from the AK-47 are arranged in a straight line, with a slight curve to the right and downwards. In the middle section, there are two long, smooth curves—first to the left and then to the right—trending slightly downwards. Only at the end of the spray does the direction become more complex, concluding with a smooth curve to the left and slightly upwards. Compared to the Galil and M4A4, considered top 2 rifles more complex, its start is more curved, and there is greater variation between ascents and descents. Regarding the Bizon spray, its complexity is evident.

Before applying complexity normalization, weapons with large magazine capacities, such as the Negev with 150 bullets and the M249 with 100 bullets, presented the highest raw complexity values. However, since the Negev spray pattern is approximately a straight line, it was concluded that raw complexity should not be used as the main comparison metric. This occurs because raw LZ complexity is strongly influenced by the length of the symbolic sequence, which is related to the number of points in the spray pattern.

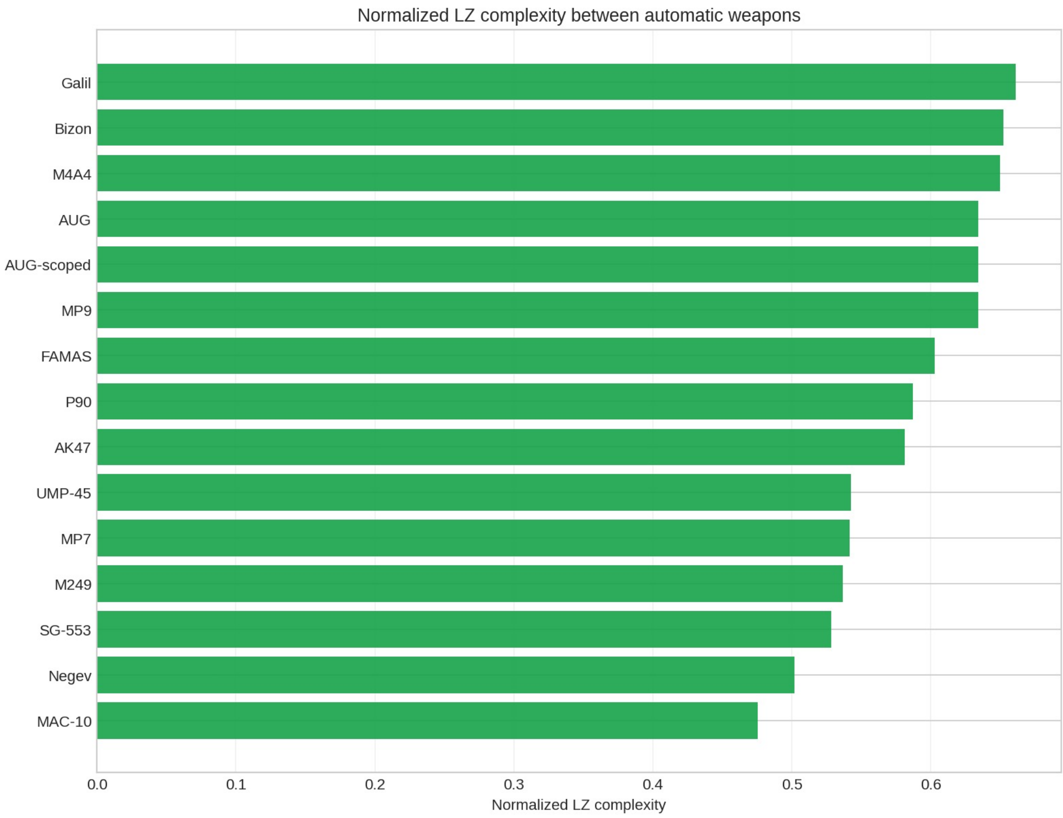

Figura 3. Normalized LZ complexity ranking among automatic weapons.

5.2. Spray Length Obtained by Professional Players

Figure 4 shows the average number of shots per spray for each weapon in the professional players' dataset. SMGs presented the longest sprays on average, followed by rifles. This result suggests that weapons with lower spray complexity, such as the MAC-10 and MP7, tend to be used in longer shooting sequences (about 35% of the spray length). On the other hand, the low variation in the number of shots between the M4A4 and the AK-47 (6.98 and 7.96) shows that a professional player has similar mastery over different spray patterns. This observation is relevant to the study of spray control, since longer sprays may require greater mastery of recoil compensation.

Additional analyses were also performed for each player, including the average number of shots per weapon and the distribution of the most frequently used weapons individually. For the MP9, which has a magazine capacity of 28 bullets, XANTARES presented an average spray length of 11 shots. For the MAC-10, with 29 bullets, kyousuke and m0NESY reached an average of 10 shots. For the MP7, also with 29 bullets, donk presented an average of 16 shots. For the M4A1, with 24 bullets, m0NESY reached an average of 8 shots. Finally, for the FAMAS, with 19 bullets, KSCERATO, YEKINDAR, and donk presented an average of 7 shots.

6. Conclusion

This work aimed to calculate the complexity of spray patterns in CS2. The comparison indicates that rifles presented the highest average normalized LZ complexity among

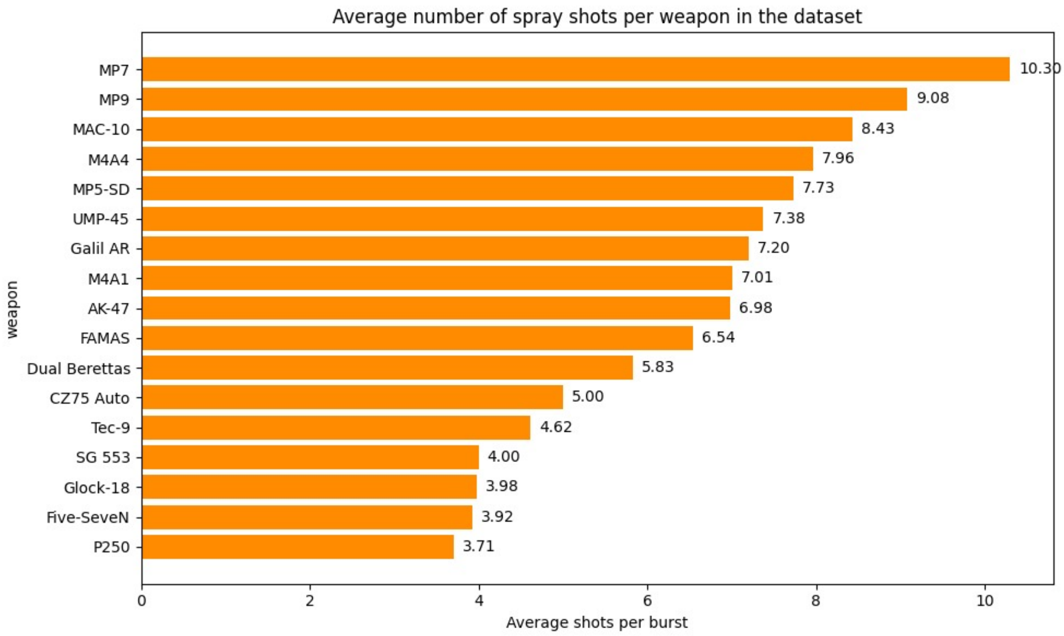

Figura 4. Average number of shots per spray for each weapon in the professional players' dataset.

automatic weapons. SMGs appeared next, followed by machine guns. The most complexity weapon was Galil (Rifle), with Bizon (SMG) and M4A4 (Rifle) in second and third places, respectively. On the other hand, MAC-10 (SMG) and Negev (Machine Gun) were considered the simplest spray pattern. The complexity of the spray pattern was visually confirmed based on the shape of the original sprays on the Leetify website.

Considering the professional players' spray lengths, result suggests that weapons with lower spray complexity, such as the MAC-10 and MP7, tend to be used in longer shooting sequence, but they are considerably smaller than the magazine capacity of the weapons and usually do not empty the full magazine during a spray, even when using weapons with relatively simple spray patterns, showing that mastering a weapon isn't that easy. Moreover, these analyses make it possible to compare playstyles and observe how the role of the player, such as rifler or AWPer, influences the quantity and type of sprays present in the dataset.

To answer the question raised in the introduction, the AK-47, the weapon most widely used by professionals, has a medium spray pattern and costs $2,700. As another example, the Galil ($1,800) is the cheapest rifle among those with complex spray patterns, while the AUG costs $3,300. We can thus conclude that there is no correlation between a weapon's cost and its complexity, and that it is possible to acquire weapons with greater firepower at lower prices.

As future works, the verification of the quality of sprays obtained by professional players (damage given or proximity to the recoil compensation points) and the comparison with spray obtained by amateur players. This type of comparison can be used by players to gauge how far they are from the best players in the world, encouraging them to train healthily in order to improve their Counter Strike careers and enhance their physical and mental health.

Referências

Durst, D., Xie, F., Sarukkai, V., Shacklett, B., Frosio, I., Tessler, C., Kim, J., Taylor, C., Bernstein, G., Choudhury, S., et al. (2024). Learning to move like professional counter-strike players. In *Computer Graphics Forum*, volume 43, page e15173. Wiley Online Library.

Kulkarni, A. R. e Kuber, P. M. (2026). Sensor-driven machine learning for cognitive state and performance risk assessment in esports: A systematic review. *Electronics*, 15(7):1465.

Kulmakorpi, T. (2025). *Effects of different physical warm-ups on the aiming performance of counter strike 2 & valorant players*. PhD thesis, University of Jyväskylä.

Lempel, A. e Ziv, J. (1976). On the complexity of finite sequences. *IEEE Transactions on information theory*, 22(1):75–81.

Marshall, S., Mavromoustakos-Blom, P., e Spronck, P. (2022). Enabling real-time prediction of in-game deaths through telemetry in counter-strike: Global offensive. In *Proceedings of the 17th international conference on the foundations of digital games*, pages 1–10.

Montalvão, J. e Canuto, J. (2014). A lempel-ziv like approach for signal classification. *TEMA (São Carlos)*, 15(2):223–234.

Wright, T., Boria, E., e Breidenbach, P. (2002). Creative player actions in fps online video games: Playing counter-strike. *Game studies*, 2(2):103–123.

Xia, X., Salinas, A., e Morstatter, F. (2025). Precision under fire: Analysis and predictive modeling in counter-strike: Global offensive. In *2025 IEEE Conference on Games (CoG)*, pages 1–8. IEEE.