Analysis of Service Returns in Table Tennis

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Abstract. This article explores the relationship between received serves and returns in table tennis by combining statistical and visual analyses. Our key findings highlight concrete patterns: for instance, **F. Zhendong** exhibits a strong dependence between serve clusters and return zones ($p < 0.001$), while **A. Lebrun** and **F. Lebrun** show no such coupling ($p = 0.176$ and $p = 0.61$ respectively). Additionally, **F. Lebrun** adapts his returns to domination phases ($p = 0.013$) and pressure levels ($p = 0.039$), and return choices are significantly associated with point outcomes for both **A. Lebrun** ($p = 0.078$) and **F. Zhendong** ($p = 0.044$). These results provide precise insights into tactical decision-making and lay the groundwork for predictive performance models.

Keywords: Sports Analytics · Table Tennis · Returns · Clustering

1 Introduction

In table tennis, service returns are the initial response by the receiver to the serves. This aspect of the game is often overlooked despite its strategic importance [7]. Unlike serves, where the player has complete control over the stroke, the receiver is constrained: they must react quickly and adapt their response based on several factors (e.g. spin, speed, and placement of the ball) within a very short time frame to influence the course of the rally.

There are various ways to respond to a serve, whether by returning in identified zones or by making a specific striking technique. While these tactical choices are crucial, they remain underdocumented in the scientific literature. Existing studies focus on serve dynamics [6], stroke biomechanics [18], or general tactics that include service returns [1], but without specifically addressing them. More in-depth tactical studies directly focus on the analysis of sequences of several strokes [19, 15]. More recently, [5] conducted a study on specific striking techniques and took serves as a study case for analysis, but none on returns. The question of how players adjust their returns based on the nature of the serves or the match context remains largely unexplored.

This article aims to explore these interactions in depth by identifying recurring patterns and tactical choices related to service returns. It provides an exploratory analysis of a substantial dataset and presents the results of statistical tests. These analyses have enabled us to identify player profiles, meaning a list of actions frequently executed in similar situations. This information serves as a foundation for developing strategies and refining players' gameplay.

Table 1: Serve types and their influence on the return.

Serve Characteristic	**Effect on Return**
Short	Restricts attacking strokes; favors controlled pushes
Long	Enables offensive topspin returns
Spin (any)	Alters ball trajectory and increases difficulty of return
Side	Limits the player's forehand/backhand options.

2 Background and Related Work

In this section, we introduce the concept of a rally, describe and illustrate the phases of the service return in table tennis (Fig. 1), and survey prior work on quantitative analyses and return strategies in racket sports.

Definition 1 (Stroke). *A stroke S occurs when a player strikes the ball validly over the net to the opponent.*

Definition 2 (Return). *A return S_1 is the stroke made by the receiver in response to the serve (S_0), in which the player strikes the ball over the net into the server's court in a valid manner.*

Definition 3 (Rally). *A rally $R = S_0, S_1, \ldots, S_n$ is a finite sequence of valid strokes per Definition 1, where S_0 is the serve and S_1 the service return. The rally concludes with S_n, after which a new rally begins.*

Definition 4 (Anticipation and reaction phase). *The anticipation and reaction phase begins slightly before the server's strike (S_0), when the receiver uses pre-impact kinematic cues to predict the ball's trajectory, and lasts until immediately after the ball's first bounce. During this interval the receiver not only formulates an early prediction of the trajectory but also adjusts their movements in response to updated sensory information [16].*

Definition 5 (Adjustment phase). *The adjustment phase covers the interval between the first and second bounces, when the receiver refines posture and footwork to optimize positioning for the return.*

Definition 6 (Decision and execution phase). *The decision and execution phase is the period from the second bounce of S_0 to the moment of contact with the ball for S_1, during which stroke selection and racket alignment are finalized.*

Serves vary along four main dimensions—length, speed, spin and side—each of which constrains the receiver's options (Table 1). Different return strokes reflect strategic intentions:

- **Push**: A defensive stroke executed by slicing under the ball resulting in a backspin. Used on backspin serves when the player cannot attack.
- **Flip**: An offensive stroke on a short ball. Applying speed and topspin.
- **Topspin**: An offensive stroke on long ball with a lot of speed and spin.

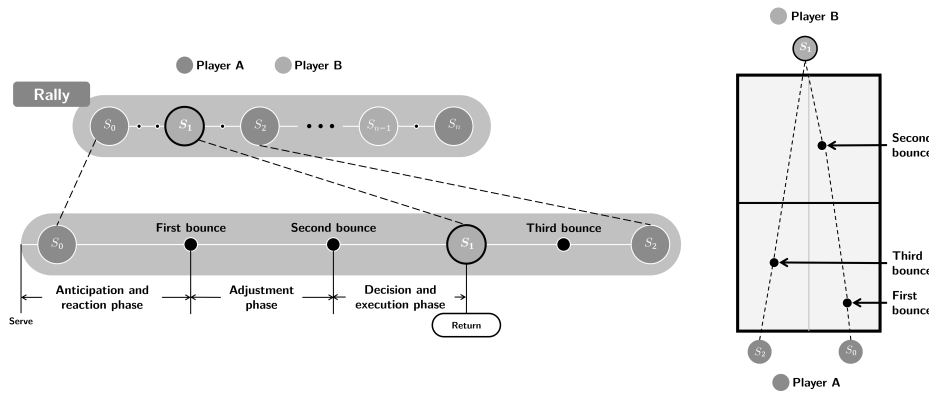


Fig. 1: Phases of the service return (left) and spatial layout of serve S_0 and return S_1 (right). Note that in this study we focus specifically on the return S_1. The anticipation and reaction phase extends from just before the serve S_0 until the ball's first bounce. The adjustment phase takes place between the first and second bounces. Finally, the decision and execution phase occurs between the second bounce and contact with the ball S_1.

Quantitative analysis in racket sports has evolved from foundational biomechanical studies to sophisticated tactical and sequence-aware modeling. Early research emphasized biomechanics, examining the physical determinants of stroke performance—for instance, trunk and wrist coordination in table tennis [18]. Subsequent work introduced spatial occupation models to assess court coverage and tactical intent [4, 20]. With the availability of richer datasets, data-driven methods became central to performance analysis: clustering techniques such as k-means were explored for pattern discovery [12], subgroup discovery methods enabled the extraction of conditional tactical rules [3], and new metrics for shot dominance and diversity were introduced to quantify serving strategies [2]. Recent advances focus on sequence-aware models that capture shot dependencies and tactical transitions using visual analytics tools for multi-shot sequences [19, 15]. These approaches align with broader insights emphasizing anticipation and adaptation as key components of competitive play [9, 8].

In table tennis, service return analysis has gained attention due to its strategic complexity: elite players exhibit greater variability and adaptability in returns [13], and a clustering-based taxonomy of serves has been proposed [6]. However, many studies still model returns in isolation, neglecting the dynamic interplay between strokes [5].

Despite these advancements, few works integrate rebound position, spin characteristics, and adaptive behavior into a unified framework. This study bridges that gap by combining clustering, tactical metrics, and sequence-aware modeling to deliver a comprehensive analysis of table tennis service returns.

3 Methods

We introduce several methods to enrich the dataset by generating clusters of return behaviors with k-means and defining two key metrics—domination, which captures transient momentum shifts via a time-decayed aggregation of past point outcomes, and pressure, which quantifies each point's contextual importance by combining factors such as score gap and match-critical situations. Using the same dataset as [5], which comprises 1,195 returns from 15 unique players, we first apply k-means clustering to categorize return patterns into distinct behavioral groups. We then define the domination and pressure metrics (presented in sections 3.3 and 3.4 respectively) and finally apply the χ^2 test to assess the dependence between return clusters and these metrics. These steps underpin our exploratory analysis and the subsequent interpretation of how players adapt their returns to evolving match dynamics.

3.1 Clustering via k-means

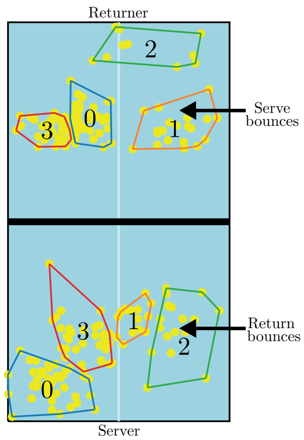
We objectively compare players' spatial return placement strategies by first segmenting rebound impact locations into distinct zones. For this purpose, we apply the k-means algorithm to the two-dimensional coordinates of return rebounds to identify spatial return zones [10, 11]. To determine the optimal value of k, we applied the elbow method to the combined match data for each studied player (**A. Lebrun**, **F. Lebrun**, and **F. Zhendong**), using the same value of k for all matches, which identifies the point where intra-cluster inertia stops decreasing significantly as the number of clusters increases. This analysis led us to select $k = 4$ as the optimal value for each player, which will be maintained throughout the study (see Fig. 9 in Appendix for **A. Lebrun**'s case as an example). Clustering is repeated over 200 random initializations as explained in Section 3.5.

The visualization of these clusters provides insights into emerging trends for each player and allows us to observe differences in playing styles. An example of such a comparison is shown in Fig. 2. In these figures, the server is always positioned at the bottom of the table, while the receiver is at the top. Consequently, the second bounces of the serves are represented in the upper half of the table, and the bounce of the service return in the lower half.

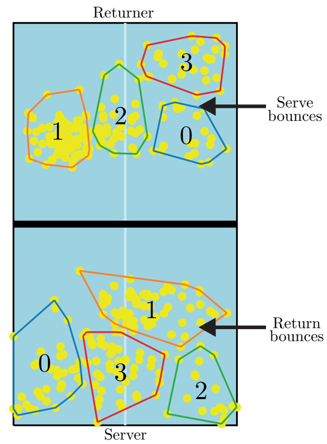
3.2 Chi-square Test of Independence

As part of this study, we aim to observe and analyze the service returns of table tennis players. To do so, it is essential to test whether return placement depends on various factors. In line with previous work on k-means clusters and χ^2 testing [17, 14].

The χ^2 test is a statistical method used to determine whether two variables are dependent or not. It measures whether the observed frequencies (derived from the data) differ significantly from the expected frequencies (those that would be observed if there were no relationship between the variables).



(a) All service returns from matches of **F. Lebrun**. Returns by **F. Lebrun** at the bottom, serves received by **F. Lebrun** at the top.



(b) All service returns from matches of **F. Zhendong**. Returns by **F. Zhendong** at the bottom, serves received by **F. Zhendong**at the top.

Fig. 2: Comparison of all returns by **F. Lebrun** on the left and **F. Zhendong** on the right. It can be observed that **F. Lebrun** is less likely to play short compared to **F. Zhendong** and tends to avoid playing long balls to the opponent's forehand.

The threshold α was set at 0.1, which is higher than the conventional value commonly used in the literature (typically 0.05). This choice is motivated by the fact that strong or clear-cut trends are rare in human behavior, and our goal is to detect even subtle patterns of effect or dependency.

3.3 Domination

A domination indicator at the scale of a set or match—taking into account tactical, physical, and psychological dimensions over an entire rally or set—has been proposed [2]. In contrast, we define a local indicator D_t depending solely on the sequence of previous point outcomes, focusing on the immediate point-by-point dynamics. This metric quantifies momentum shifts during a match, offering insight into player behavior on returns. Indeed, table tennis matches feature key moments where one player dominates—imposing rhythm, scoring consecutively, and pressuring the opponent. Capturing these phases with a performance indicator would help analyze return behavior in relation to momentum shifts.

We define a local domination indicator D_t to capture transient control during a match. For a match between player A and player B at time t:

$$D_t = \sigma\left(\sum_{i=1}^{t-1} \beta_{t-i} V_{t-i}\right), \quad \beta_j = \frac{5 \cdot j^p}{\sum_{i=0}^{t-1} i^p}, \quad \sigma(x) = \frac{1}{1+e^{-x}},$$

where $V_j = +1$ if A won point j (else -1), and weights β_j decrease with time to emphasize recent points. We categorize $D_t > 0.6$ as A dominating, $D_t < 0.4$ as B dominating, else neutral. A significant χ^2 test on the contingency of "dominant player" vs. return cluster indicates if players adapt returns to domination phases.

3.4 Pressure

During a table tennis match, certain points carry particular significance. For example, a set point is far more critical to defend than a simple point played when the score is 5–3 and one player is already leading by 2 sets to 0.

To capture such nuances, we model point-by-point pressure by combining sub-indicators:

$$\begin{aligned}
\text{pressure}_{\text{score}} &= \frac{1}{1+\text{score_gap}}, \\
\text{pressure}_{\text{set_end}} &= \frac{1}{1+|10-\min(10,\max(s_A,s_B))|}, \\
\text{pressure}_{\text{key_moments}} &= \begin{cases} 1, & \text{if set/match point with gap} < 2 \\ 0, & \text{otherwise} \end{cases}, \\
\text{pressure}_{\text{set}} &= \frac{1}{1+\text{set_gap}}, \\
\text{pressure}_{\text{decisive_set}} &= \begin{cases} 1, & \text{in decisive set} \\ 0, & \text{otherwise} \end{cases},
\end{aligned}$$

with s_A and s_B representing the scores of players A and B, respectively. These combine as

$$\text{pressure}_{\text{total}} = \sum_{i=1}^{5} \alpha_i \cdot \text{sub\_indicator}_i,$$

with $(\alpha_1, \alpha_2, \alpha_3, \alpha_4, \alpha_5) = (2.25, 2.25, 2.25, 0.75, 2.50)$. We then test independence between pressure-level bins and return clusters via χ^2.

3.5 Initialization Robustness

To ensure that our k-means results are not sensitive to centroid seeds, we repeat the clustering procedure over 200 independent random initializations.

The choice of 200 initializations was established after analyzing the convergence of characteristic metrics (mean, variance, and confidence interval bounds at 95%) as a function of the number of iterations. We observed that beyond 200 initializations, these metrics showed negligible variation, ensuring the stability and reliability of the obtained results.

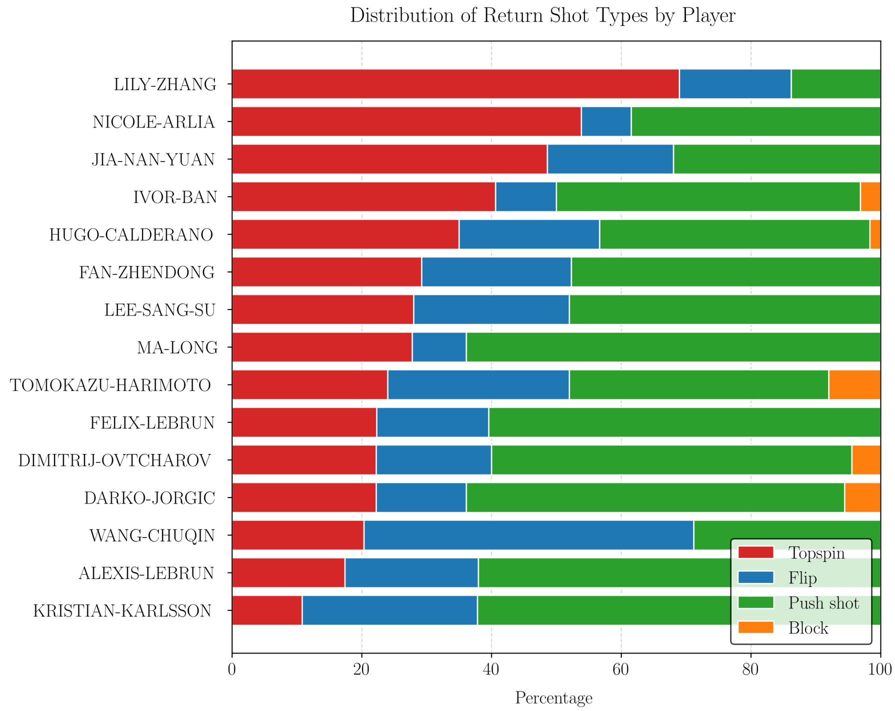


Fig. 3: Distribution of return types by player. **Lily Zhang** executes the most topspin shots, while **Kristian Karlsson** executes the fewest. Meanwhile, **Wang Chuqin** performs the most flip shots.

4 Exploratory Analysis

Fig. 3 provides a visual summary of the data, with players sorted based on the percentage of topspin returns. It shows the proportion of different return shot types—topspin (red), flip (blue), push slice (green), and block (orange)—used by each player. While this visualization provides an overview of shot preferences, interpreting it requires caution due to several contextual factors.

For instance, **Wang Chuqin** uses a high proportion of flips compared to other players. However, this statistic alone does not indicate effectiveness, as many of these flips may have occurred in unfavorable conditions forced by the opponent's serves. Specifically, certain types of serves can compel a player to flip under pressure or from a less advantageous position, reducing the success rate of these returns. Thus, integrating win/loss statistics on points following each shot type would be critical to evaluate the true tactical value of these shots.

Players with a higher proportion of blocks might be reacting to long serves that surprise them, limiting their options to a defensive block. Understanding whether these blocks are predominantly responses to long serves could provide insights into the effectiveness of serving strategies targeting specific return zones. Distinguishing between long and short pushes would enhance this analysis, as each imposes different tactical constraints and demands different return techniques.

Overall, the figure reveals shot-type tendencies but requires complementary data—such as the location and spin of serves and the outcome of the points—to fully interpret how these return types relate to the players' strategic responses and match dynamics.

5 Results

We now report our main findings through four complementary analyses: the dependence between serve placement and return zones; the relationship between return clusters and point outcomes; the adaptation of return choices during domination phases; and the influence of match pressure on return behavior.

Dependence between Return Clusters and Received Service Clusters

We constructed contingency tables of received-serve cluster versus return-cluster assignments for three players (**A. Lebrun**, **F. Lebrun**, **F. Zhendong**) and applied χ^2 test of independence with $\alpha = 0.10$. For **A. Lebrun**, $p = 0.176$ indicating no significant dependence between serve placement and return zone. **F. Lebrun** similarly shows $p = 0.61$, also non-significant. In contrast, **F. Zhendong**'s test returns $p < 0.001$, demonstrating a strong strategic association between serve clusters and chosen return zones (Fig. 4).

The figure illustrates the spatial distribution of return positions (right) depending on the combination of serve and return clusters, summarized in the contingency table (left). On the court diagram, colored regions represent the different return clusters, each marked by a number (0–3). These clusters are distinct from the serve clusters, which are also labeled 0–3, indicating that return positioning is influenced by serve patterns but follows its own clustering logic.

It is important to note that the numbering of serve clusters (rows) and return clusters (columns) are independent — cluster 1 for serves is not the same as cluster 1 for returns. The table shows the number of points observed for each combination of serve and return clusters. A particularly notable pattern appears for Serve cluster 1 and Return cluster 1: this combination accounts for 33 points — by far the highest frequency in the matrix. This indicates a strong relationship: when the serve falls into cluster 1, which is a short serve in the forehand of **F. Zhendong**, the returner tends to respond from within return cluster 1, which is a short return which is a cross-court return. This spatial and tactical alignment suggests a predictable return behavior influenced by the serve's characteristics.

Dependence between Point Winners and Return Clusters

To determine which return zones favor point wins, we analyze contingency tables of winners versus return clusters. **A. Lebrun**'s test yields $p = 0.078$, indicating dependence: his most effective zone is cluster 3 (23 vs. 19 wins), whereas cluster 2 under-performs (16 vs. 20) (Fig. 5). **F. Lebrun**'s $p = 0.645$ shows no significant association, reflecting uniform effectiveness across clusters. **F. Zhendong**'s $p = 0.044$ confirms a significant relationship: clusters 2 (8 vs. 4) and 0 (21 vs. 15) are most successful, while cluster 1 yields fewer wins (18 vs. 23) (Fig. 6).

Dependence between Domination and Return Clusters

This analysis tests whether a player's domination phase (self, opponent, or neither) affects the choice of return cluster. We construct contingency tables of domination status versus return clusters.

For **A. Lebrun**, $p = 0.858$ indicates no significant dependence, suggesting his return zones remain stable across domination phases. **F. Lebrun** shows $p = 0.013$, revealing a significant association: he favors cluster 1 when dominating (16 occurrences) and cluster 2 when dominated (22) (Fig. 7). **F. Zhendong**'s $p = 0.285$ likewise indicates no dependence, implying his return choices are unaffected by who is dominating.

These findings demonstrate that only **F. Lebrun** adapts his return zones according to domination dynamics, whereas **A. Lebrun** and **F. Zhendong** maintain consistent placement regardless of match control. Notably, when **F. Lebrun** is under pressure, he tends to select cluster 2, which corresponds to a short zone on the opponent's forehand side (assuming a right-handed opponent), likely to avoid a backhand flip—typically more effective and easier to execute than a forehand flip.

Dependence between the Pressure and the Return Clusters

We examine whether the level of pressure influences return–cluster choices by constructing contingency tables and applying Pearson's chi-square test at $\alpha = 0.10$. For **A. Lebrun**, $p = 0.92$ indicates no significant dependence, suggesting his return selections remain consistent across pressure levels. In contrast, **F. Lebrun**'s $p = 0.039$ reveals a significant association: he favors cluster 1 under low or medium pressure (12 and 20 occurrences, respectively) and reduces risk under high pressure by choosing shorter returns in clusters 0 and 2 (Fig. 8). Finally, **F. Zhendong** yields $p = 0.12$, showing no statistical dependence, although he tends toward long-body returns when pressure peaks. Only **F. Lebrun** demonstrates a pressure-driven adaptation in return zones.

Summary of Independence Results

Table 2 summarizes the statistical independence results presented in the previous sections.

Table 2: Independence test results (p-values and interpretation) for each player and for each test

Player	**Service ↔ Return**	**Winner ↔ Return**	**Dominance ↔ Return**	**Pressure ↔ Return**
F. Lebrun	$p = 0.61$ Independence	$p = 0.645$ Independence	$p = 0.013$ **Dependence**	$p = 0.039$ **Dependence**
A. Lebrun	$p = 0.176$ Independence	$p = 0.078$ **Dependence**	$p = 0.858$ Independence	$p = 0.92$ Independence
F. Zhendong	$p < 0.001$ **Dependence**	$p = 0.044$ **Dependence**	$p = 0.285$ Independence	$p = 0.12$ Independence

Activity-Centered Interpretation

Beyond the statistical relationships uncovered through χ^2 tests, we propose a complementary reading based on the activity-centered approach, commonly used in sports science to interpret athlete behavior in terms of motor adaptation, strategic learning, and individual predispositions.

For example, **F. Zhendong**'s strong dependence between serve and return clusters may reflect a form of expertise developed through targeted and repeated training of fixed serve–return sequences. Such consistency suggests a highly internalized tactical schema reinforced through structured practice. This aligns with the common perception of Chinese players as highly regular and efficient, favoring reliable and optimized routines over variability.

In contrast, **A. Lebrun** and **F. Lebrun** exhibit no significant dependence at the match level ($p = 0.176$ and 0.61, respectively), which could indicate a more flexible or unpredictable return strategy. This is consistent with their reputation for creative play—often deliberately avoiding repetition and seeking to vary their responses point after point. Rather than reflecting a lack of structure, this variability appears to be a deliberate tactical approach, integral to their playing identity.

When considering contextual dynamics, **F. Lebrun** shows significant variation in his return choices depending on whether he is dominating or under pressure. This suggests an adaptive behavior that may stem from a natural tactical sensitivity—often described as "game sense" or an instinctive feel for the game. Interestingly, this context-dependent adaptation contrasts with his otherwise variable style, suggesting that **F. Lebrun** modulates his creativity in response to match situations.

By contrast, **A. Lebrun** and **F. Zhendong** do not significantly modify their return zones under pressure or domination, which may reflect a more stable tactical model—potentially the result of deliberate training routines aimed at ensuring consistency regardless of context. In that sense, **F. Lebrun** appears to rely more heavily on in-the-moment adjustments, dynamically adapting his behavior to the flow of the match, which may reflect a different kind of expertise—less standardized, and more emergent.

From an activity-based viewpoint, the observed return behaviors can be interpreted as the result of two complementary forces: structured training protocols (consistent, rehearsed responses) and innate or cultivated abilities (creative, intuitive adjustments). These findings highlight not only individual differences but also stylistic choices that are deeply embedded in each player's tactical philosophy.

6 Conclusion

We contributed to novel insights on service returns in table tennis, by employing statistical methods and clustering techniques such as k-means. The findings reveal that the relationship between the type of serve and subsequent return varies notably across players. For instance, while **F. Zhendong** exhibits a clear and predictable correlation between service clusters and his return behavior—indicative of a highly calculated approach—**A. Lebrun** and **F. Lebrun** display more diverse or context-dependent return patterns. Moreover, the investigation into the influence of match pressure and domination phases further underscores how situational dynamics can shape the tactical responses. Our code and data are publicly released[1] for transparency and reproducibility purposes.

These results not only enhance our understanding of the underlying strategies but also pave the way for developing predictive models aimed at optimizing players' performance. Future research could build upon these findings by incorporating additional variables and exploring inter-individual differences in greater depth.

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Appendix

Serve \ Return	**0**	**1**	**2**	**3**
0	14	2	0	2
1	8	33	10	19
2	6	5	0	2
3	8	1	2	3

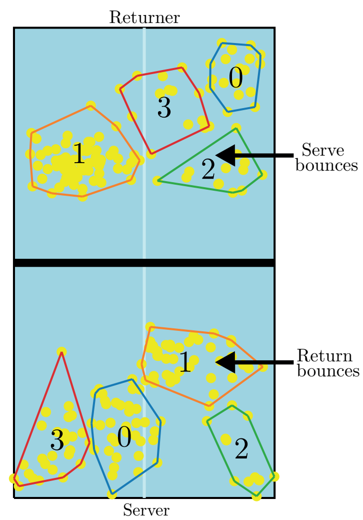

Fig. 4: On the left, the contingency table shows the relationship between serve and return clusters for **F. Zhendong**. On the right, all his service returns are displayed, with returns positioned at the bottom and received serves at the top.

Winner \ Return	**0**	**1**	**2**	**3**
A. Lebrun	18	28	16	23
Opponent	18	30	20	19

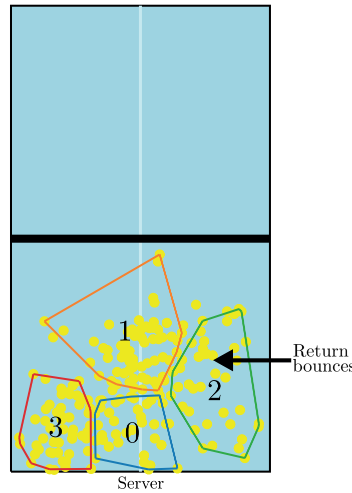

Fig. 5: On the left, contingency table representing the data used to study the dependence between return clusters and point winners for **A. Lebrun** on return. On the right, all service returns from matches of **A. Lebrun**.

Winner \ Return	**0**	**1**	**2**	**3**
F. Zhendong	21	18	8	15
Opponent	15	23	4	11

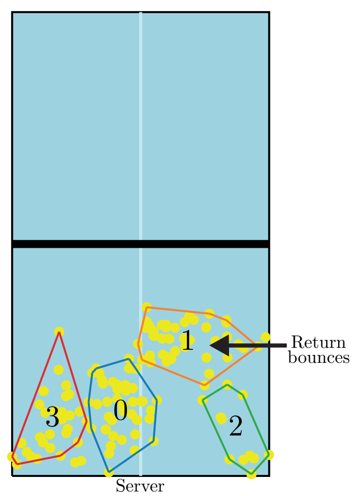

Fig. 6: On the left, contingency table representing the data used to study the dependence between return clusters and point winners for **F. Zhendong** on return. On the right, all service returns from matches of **F. Zhendong**.

Dominant \ Return	0	1	2	3
F. Lebrun	9	16	6	7
Opponent	11	17	22	7
Nobody	5	6	4	11

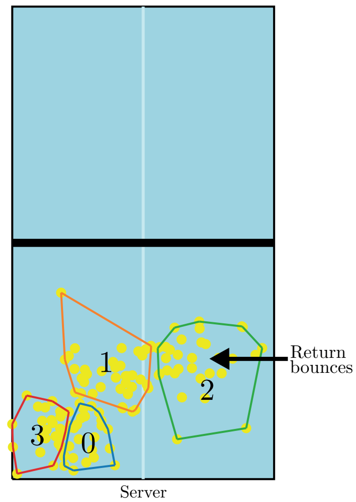

Fig. 7: On the left, contingency table representing the data used to study the dependence between return clusters and the player in a phase of domination for **F. Lebrun** on return. On the right, all service returns from matches of **F. Lebrun**.

Pressure \ Return	0	1	2	3
Low	7	12	5	12
Medium	9	20	4	2
Fairly High	11	9	4	2
High	6	5	1	5

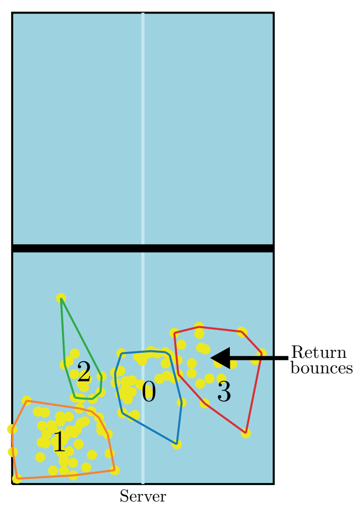

Fig. 8: On the left, contingency table representing the data used to study the dependence between return clusters and pressure for **F. Lebrun** on return. On the right, all service returns from matches of **F. Lebrun**.

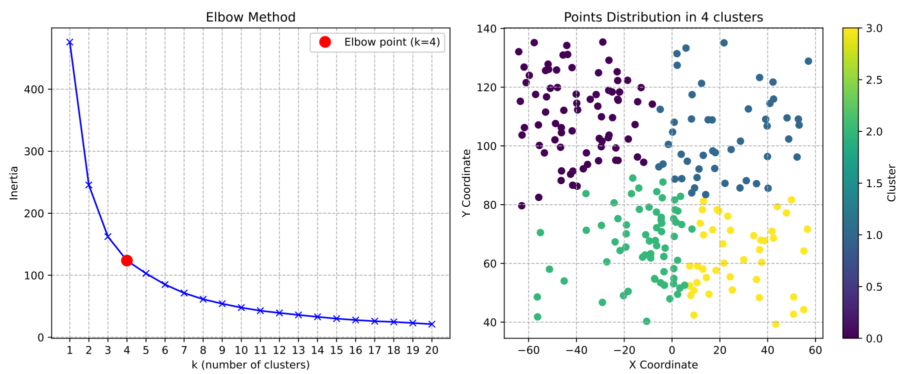

Fig. 9: Analysis of **A. Lebrun**'s service returns clustering using the elbow method. Left: Evolution of inertia as a function of the number of clusters (k), showing the elbow point that suggests the optimal number of clusters. Right: Spatial distribution of service return points colored by their assigned cluster, after outlier removal and coordinate normalization. Each cluster represents a distinct pattern in **A. Lebrun**'s return strategy.