Pickleball Analytics: Research Directions for a Fledgling Sport

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Abstract

This paper outlines the current state of affairs in pickleball analytics. In addition to the review, we speculate on promising directions for the future of pickleball analytics. Several new strategic results are also developed. In particular, we provide a suggestion that counters traditional practice. Probabilistically, it is argued that a mild creep immediately after serving is advantageous.

Keywords: pickleball, sports analytics, tactics.

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1 INTRODUCTION

Although the sport of pickleball was invented in 1965, it has recently experienced a dramatic increase in popularity. For example, in each of the years 2021, 2022, 2023 and 2024, pickleball was identified as the fastest growing sport in the United States with an estimated 19.8-48.3 million players in 2024 (Mackie 2025). The sport is now played worldwide, and professional tours such as the PPA (Professional Pickleball Association) and the MLP (Major League Pickleball) have helped grow the sport.

With the surge in popularity of pickleball, aspects of the sport are evolving. Evolution takes various forms including the development of advanced equipment, rule changes and improved playing facilities. It may also be expected that the sport will see increased activity in pickleball analytics. Pickleball analytics may be thought of as the use of data and quantitative reasoning to impact the way the game is played.

This paper reviews the current state of pickleball analytics. At the time of writing, the literature on pickleball analytics is sparse. Despite a huge number of pickleball books, the monograph "Pickleball Moneyball" (Swartz 2024) appears to be the only attempt from an analytics perspective. The text by Albert et al. (2017) overviews analytics across major sports.

Lately, there have been several disparate pickleball contributions in the broader analytics literature. Gill and Swartz (2019) use match data and develop a Bayesian model where it is suggested that pickleball is a strong link sport. That is, outcomes in doubles pickleball are more affected by a team's stronger player than the team's weaker player. Steyn et al. (2025) examine flight dynamics in pickleball and conclude that successful drop shots are more dependent on the speed and angle of shots rather than spin. The authors have also developed a GUI where pickleball flight paths can be simulated. The GUI is soon to be posted on the website of the *Jericho Hill Pickleball Society* (https://jerichohillpickleball.com). Emond, Sun and Swartz (2024) also consider pickleball flight dynamics with the additional consideration of wind. They suggest a counterintuitive result that it is advantageous to play against the wind rather than with the wind in mild wind conditions. Gandhi (2024) provides interesting statistics from collecting data on various pickleball players where the players are categorized according to skill level. For example, Gandhi (2024) reports the win percentage from hitting deep and shallow returns. Interestingly, deep returns are preferred, and are more beneficial at higher skill levels. Swartz and Tang (2025) use methods from experimental design to develop optimal tournament schedules.

We review and extend some of the contributions listed above. Also, we speculate on potential areas of future activity in pickleball analytics.

In the related sport of tennis, the analytics literature is more mature, and may provide insights as to how pickleball analytics may develop. For example, Klassen and Magnus (2001) investigated the assumption that points are independent and identically distributed. They concluded that point outcomes are positively correlated and that servers are less likely to win a point in important situations. For assessing performance and forecasting, papers by Baker and McHale (2014, 2017) and McHale and Morton (2011) applied the classical Bradley-Terry model. Kovalchik (2016) studied 11 forecasting models in tennis for the purposes of match prediction. More recently, tracking data have been used to gain insights on tennis. Tea and Swartz (2023) investigated serving tendencies which may allow a player to anticipate the nature of the opponent's serve. The approach relies on hierarchical models in a Bayesian framework. Kovalchik and Albert (2022) investigated serve returns by introducing a semiparametric mixture model. Epasinghege Dona, Gill and Swartz (2025) studied aspects of rally length where they developed a trivariate outcome model related to each touch. Peiris, Epasinghege Dona and Swartz (2025) analyzed the impact of unforced errors in tennis.

1.1 The Sport of Pickleball

We first provide a short description of the basics of pickleball. More detailed information on the rules can be found in the Global Pickleball Federation Official Rulebook (2025).

Pickleball is a net sport that is sometimes thought of as an amalgam of tennis, badminton and ping pong. Pickleball paddles vary in size and shape, and are typically made from composite materials. Paddles are about 16 inches long and 8 inches wide, weighing between 7 and 10 ounces. The ball is a "wiffle ball", weighing less than one ounce. Pickleball may be played either indoors or outdoors on courts that are 44 feet long and 20 feet wide, less than half the area of a tennis court. The pickleball net is 36 inches tall at the sides and 34 inches tall in the middle.

The most popular form of pickleball is doubles pickleball where matches are scored to

11 points with a requirement that a team must win by at least two points. Only the serving team can score. A valid serve must land in the serving area, and neither the first shot (the serve) nor the second shot can be volleyed; i.e. - the ball must be allowed to bounce. The ball may bounce at most once. A rally is lost when a team does not return a shot into the designated landing area. A unique feature of pickleball concerns "the kitchen"; i.e. the non-volley zone. On each side of the net, this is the 7-foot region where teams are not allowed to volley the ball. The rationale is that it would be too easy to win a rally if players were allowed to strike the ball if they were positioned immediately adjacent to the net.

2 CONSIDERATIONS OF STRATEGY

There are many strategic decisions that are made during a pickleball match. For example, should a player hit a drive or a drop shot? Should a player hit a wide shot or a shot down the middle?

Although there is much anecdotal advice involving strategies, decision making is rarely couched in the language and the consideration of probability. Using a probabilistic lens, strategic choice is straightforward. Strategy A ought to be preferred over Strategy B if the probability of winning a rally under A is greater than the probability of winning the rally under B. Of course, there is always the mitigating issue in sports that players should not allow themselves to become predictable. Swartz (2024) developed a probabilistic framework for comparing pickleball strategies; the approach is described below and is illustrated in two new pickleball scenarios.

In this probabilistic framework, we denote W_A as the probability of winning a rally under Strategy A. We also denote a partition of events $(A_1, \ldots, A_n)$ associated with Strategy A. Then, using the *total law of probability*, the probability of winning the rally under A is given by

$$\begin{aligned} \text{Prob}(W_A) = \; &= \sum_{j=1}^{n} \text{Prob}(W_A, A_j) \\ &= \sum_{j=1}^{n} \text{Prob}(W_A \mid A_j)\ \text{Prob}(A_j)\ . \qquad (1) \end{aligned}$$

For a non-technical person, an important point to keep in mind is that equation (1) is not debatable. It is a fact of science, as unequivocal as the law of gravity. What is debatable are the probabilities that are assigned on the right hand side of equation (1). These probabilities are generally unknown and depend on both the abilty of the player in question and the opponents. However, these probabilities are introduced in what may be thought of as a divide-and-conquer scheme. It is easier to assign the component probabilities than to try to assess $\text{Prob}(W_A)$ outright. A major obstacle in current pickleball analytics is the lack of data available to inform the component probabilities in equation (1). In Section 5, the data issue is discussed further.

In the following subsections, we illustrate the use of the total law of probability (1) when deciding between competing pickleball strategies. The results have not been previously obtained. The probabilistic approach presented here may be used in future work involving decision making in pickleball.

2.1 To Creep or not to Creep

Conventional pickleball strategy suggests that upon serving, the serving team should remain behind the baseline until the second shot has been played. The rationale is that by rule, the serving team must allow the second shot to bounce. If a player on the serving team were to rush forward, then a deep second shot would pose great difficulty. The player would be moving forward, and would need to backpedal, allowing the shot to bounce.

Moving forward immediately after the serve is sometimes referred to as "creeping". The advantage of creeping occurs when the second shot is not hit deep. Creeping allows a player on the serving team to meet the second shot earlier and to more quickly approach the *non-volley zone* which is known to be an advantageous court position.

Using the probabilistic approach described above, we denote the strategies C and NC as creeping and not creeping, respectively. The easier of the two required derivations is

$$\text{Prob}(W_{NC}) = 0.40 \ . \tag{2}$$

Note that the assigned probability in (2) depends on both the characteristics of the player and the opponents. Equation (2) states that the probability of winning a rally when the serving team is not creeping is 0.40. In a match against comparable opponents, this may be a reasonable value since it is known that the serving team is slightly disadvantaged compared to the returning team. Of course, it is possible to substitute a value other than 0.40 to satisfy particular circumstances.

We now derive the second required probability. Using the total law of probability (1), we have

$$\begin{aligned} \text{Prob}(W_C) &= \text{Prob}(W_C \mid \text{2nd safe}) \text{ Prob}(\text{2nd safe}) \\ &+ \text{Prob}(W_C \mid \text{2nd baseline}) \text{ Prob}(\text{2nd baseline}) \\ &+ \text{Prob}(W_C \mid \text{2nd OB}) \text{ Prob}(\text{2nd OB}) \\ &= 0.45(0.9) + 0.20(0.05) + 1.0(0.05) \\ &= 0.47 \end{aligned} \tag{3}$$

In (3), we have defined a partition corresponding to the different types of second shots that are relevant to the serving team. A second shot may be "safe" in the sense that it may be placed somewhere near the middle of the designated landing area. Alternatively, a second shot may be aggressive and lands near the baseline. It is important to identify this type of shot because it causes difficulty for players on the serving team when they are creeping. The third type of shot is one that is "OB" - out of bounds. This may happen if the returner is hitting an aggressive baseline shot, accidently hits it too hard and it lands beyond the baseline.

We have provided plausible values for the six component probabilities on the right hand side of equation (3). Again, values should be provided that are appropriate for personal circumstances. In particular, we have stipulated that safe second shots occur 90% of the time, and that the remaining two cases (baseline second shots and OB second shots) each occur 5% of the time. We have assigned the probability $\text{Prob}(W_C \mid \text{2nd safe}) = 0.45$ which states that the serving team wins the rally 45% of the time when they are creeping and a safe second shot is played. It makes sense that this probability is greater than the probability 0.40 in (2) - this is the advantage due to creeping when a safe second shot is hit. We also assign $\text{Prob}(W_C \mid \text{2nd baseline}) = 0.20$ which states that the serving team only wins 20%

of rallies when they are creeping and a second shot is played which lands near the baseline. This low probability highlights the risk of creeping. Note that we are considering the case of “mild” creeping where the serving team only goes beyond the baseline one or two steps, so that they have a chance to recover. Fortunately, the resulting probability $\text{Prob}(W_C)$ is not overly sensitive to the specification $\text{Prob}(W_C \mid \text{2nd baseline}) = 0.20$. If 0.20 is replaced with 0.10, the resulting probability is 0.46 which remains close to $\text{Prob}(W_C) = 0.47$.

Now, since $\text{Prob}(W_C) = 0.47 > \text{Prob}(W_{NC}) = 0.40$, we conclude that moderate creeping is a better strategy than the traditional practice of not creeping. This result is counter-intuitive to what many pickleballers believe.

Our intuition suggests that assigned probabilities in the above analysis are widely applicable. However, it should be emphasized that the assigned probabilities $\text{Prob}(W_{NC})$, Prob(2nd safe), Prob(2nd baseline), Prob(2nd OB), $\text{Prob}(W_C \mid \text{2nd safe})$, and $\text{Prob}(W_C \mid \text{2nd baseline})$ are player dependent. For individual players, they should substitute probabilities that are relevant to their playing characteristics. Modifying the values and analyzing the impact of new values provides a *sensitivity analysis.*

2.2 To Drop or to Lob

Consider a player who is near the baseline and a shot has been played towards them. The opponents have reached the non-volley zone, and the player is in a vulnerable position. At this stage, there are various options for the type of return shot. In particular, the player may hit a drive, a lob or a drop. Although nothing prevents us from considering all three options, for ease of presentation, we compare the drop shot versus the lob shot.

Under our probabilistic framework, we denote a drop by D and a lob by L. Using the total law of proability for the drop shot, we write

$$\begin{aligned} \text{Prob}(W_D) &= \text{Prob}(W_D \mid \text{net})\ \text{Prob}(\text{net}) \\ &+ \text{Prob}(W_D \mid \text{perfect})\ \text{Prob}(\text{perfect}) \\ &+ \text{Prob}(W_D \mid \text{high})\ \text{Prob}(\text{high})\ . \end{aligned} \tag{4}$$

In (4), the partition is defined according to the type of drop shot by the player of interest; either into the net, a perfect drop or a drop that is high. We identify these events in the partition since they greatly affect subsequent play. For example, a high drop shot allows the opponents to stand at the edge of the non-volley zone, and easily hit a winning shot by angling the shot downward, and typically with power. On the other hand, a perfect drop is a drop shot that just clears the net. A perfect drop shot makes it difficult for the opponent to hit a challenging return shot. Although there are other possible types of drop shots, we have identified the three main classes.

Our task is to assign realistic values to the six component probabilities on the right hand side of equation (4). Again, the value of the probabilities depend on the player and the opponents. For illustration, let's assume that the players are of roughly equal ability.

We now simplify the expression on the right hand side of equation (4). First, if the ball is hit into the net, the rally is lost and therefore $\text{Prob}(W_D \mid \text{net}) = 0$. Second, if the drop shot is hit perfectly, both teams will have reached the non-volley zone, and from that stage of the rally, the teams are on an equal footing; i.e. $\text{Prob}(W_D \mid \text{perfect}) = 1/2$. Third, let's assume that the two types of imperfect drop shots occur at the same rate, i.e. $\text{Prob}(\text{net}) = \text{Prob}(\text{high})$. Putting these simplifications together, equation (4) reduces to

$$\text{Prob}(W_D) = \text{Prob}(\text{perfect})/2 + \text{Prob}(W_D \mid \text{high})(1 - \text{Prob}(\text{perfect}))/2 \;. \tag{5}$$

There are two unknown terms in equation (5) that need to be determined. If the ball is hit high, the opponent will slam the ball back (i.e. hit it with power) and the rally is likely lost. We therefore consider two plausible values, $\text{Prob}(W_D \mid \text{high}) = 0.1, 0.4$. For hitting perfect drops, there is a range of skill levels, and we consider $\text{Prob}(\text{perfect}) = 0.2, 0.4, 0.6, 0.8$.

For the lob shot, we also have a probabilistic expression

$$\begin{aligned} \text{Prob}(W_L) &= \text{Prob}(W_L \mid \text{short}) \; \text{Prob}(\text{short}) \\ &+ \text{Prob}(W_L \mid \text{OB}) \; \text{Prob}(\text{OB}) \\ &+ \text{Prob}(W_L \mid \text{good}) \; \text{Prob}(\text{good}) \;. \end{aligned} \tag{6}$$

In (6), the partition is defined according to the type of lob shot by the player of interest; either a short lob, a lob that goes out of bounds or a good lob. As before, we simplify equation (6). First, an OB lob results in a lost rally, i.e. $\text{Prob}(W_L \mid \text{OB}) = 0$. Second, let's assume that the two types of bad drop shots occur at the same rate, i.e. $\text{Prob}(\text{short}) =$

Prob(OB). Putting these simplifications together, equation (6) reduces to

$$\text{Prob}(W_L) = \text{Prob}(W_L \mid \text{short})(1 - \text{Prob}(\text{good}))/2 + \text{Prob}(W_L \mid \text{good})\text{Prob}(\text{good}) \ . \quad (7)$$

Finally, there are three unknown terms in equation (7) that need to be determined. We consider the following range of plausible values: Prob(good) $= 0.5, 0.8$, Prob(W_L | short) $= 0.1, 0.4$, Prob(W_L | good) $= 0.5, 0.8$.

We now compare equation (5) with equation (7) under the suggested plausible settings. The results are provided in Table 1. For many, the results may appear shocking since the results from lob shots are comparable, if not better than the results from drop shots. In pickleball, drop shots are the shots that are widely lauded and are regarded as the trademark of good play. Of course, the settings in Table 1 may be unrealistic for many players. If a player does not execute lob shots frequently, their component probabilities could be much different. For example, if we set Prob(good) $= 0.3$, Prob(W_L | short) $= 0.1$ and Prob(W_L | good) $= 0.3$, then the probability of winning a rally from a lob is only Prob(W_L) $= 0.125$. This example highlights the importance of knowing your execution levels when determining strategy.

Drop Settings		P(W_D)	Lob Settings			P(W_L)
P(W_D | high)	P(perfect)		P(good)	P(W_L | short)	P(W_L | good)	
0.1	0.2	0.140	0.5	0.1	0.5	0.275
0.1	0.4	0.230	0.5	0.1	0.8	0.425
0.1	0.6	0.320	0.5	0.4	0.5	0.350
0.1	0.8	0.410	0.5	0.4	0.8	0.500
0.4	0.2	0.260	0.8	0.1	0.5	0.410
0.4	0.4	0.320	0.8	0.1	0.8	0.650
0.4	0.6	0.380	0.8	0.4	0.5	0.440
0.4	0.8	0.440	0.8	0.4	0.8	0.680

Table 1: Probability of winning a rally from a drop shot (equation (5)) and probability of winning a rally from a lob (equation (7)) calculated under various settings. For concise presentation, Prob has been replaced with P.

There is also an instructive aspect regarding Table 1 and the formulae provided in equation (5) and equation (7). When you substitute probabilities into the equations, it provides opportunity for assessment. It allows you to determine weaknesses and strengths in your game. For example, you might check what difference it makes in winning a rally based on a drop shot if you change the probability of executing a perfect drop P(perfect) from say 0.4 to 0.8. This may inform points of emphasis during drilling (practice).

3 TOURNAMENT DESIGN

Scheduling is a broad topic which has a prominent role in sport (Ribeiro, Urrutia and de Werra 2023). Leagues need to determine schedules based on constraints. Constraints are varied and may include the use of shared facilities, a balance between home and road games, specified numbers of matches against teams in one's division, maximum number of schedule games over fixed timespans, etc.

The scheduling of pickleball tournaments is not as complex as in the major sports. However, there are often subtleties associated with pickleball that impact tournament design. This suggests an avenue for future work where the subtleties are addressed. Currently, pickleball tournament design borrows from existing designs such as schedules for double knockout tournaments.

An example of a peculiarity in pickleball occurs with "scramble" tournaments. A scramble tournament is more of a social tournament in doubles pickleball where a player does not have a fixed partner. Rather, during rounds of a tournament, a player will find themself paired with and against different players. If partners and opponents are drawn randomly in each round, then it is likely that a player will have repeat partners/opponents. Even though a scramble tournament is mostly social, some people find this to be unfair.

A solution for a particular scramble tournament was developed by Swartz and Tang (2025). In their work, they consider tournaments of N players competing across n rounds. That is, in each round, there are $N/4$ matches taking place where each match involves four players. Swartz and Tang (2025) use theory from resolvable balanced incomplete block designs to obtain tournament schedules.

A proposed tournament design for the case ($N = 16$, $n = 5$) is presented in Table 2. The optimal feature of this design is that each competitor plays with every other competitor (either as a partner or as an opponent) exactly once.

Round	Team 1		Team 2	
1	1	2	3	4
1	5	6	7	8
1	9	10	11	12
1	13	14	15	16
2	1	5	9	13
2	2	6	10	14
2	3	7	11	15
2	4	8	12	16
3	1	6	11	16
3	2	5	12	15
3	3	8	9	14
3	4	7	10	13
4	1	7	12	14
4	2	8	11	13
4	3	5	10	16
4	4	6	9	15
5	1	8	10	15
5	2	7	9	16
5	3	6	12	13
5	4	5	11	14

Table 2: The proposed assignment of partners and opponents in the case of ($N = 16$ players, $n = 5$ rounds) taken from Swartz and Tang (2025).

4 ASSESSING PLAYER STRENGTH

It is frequently stated that pickleball players enjoy their sport the most when they are competing against players of comparable ability.

To assist in assessing ability, the DUPR (Dynamic Universal Pickleball Rating) system has been developed. When players compete in a sanctioned match, the result of the match is reported and the DUPR ratings of the players are updated. A nice feature of DUPR is that it is free to use. In theory, DUPR ratings range from 2.0 to 8.0. Roughly, one half of DUPR-rated players have DUPR ratings below 3.5, and only top professionals have DUPR ratings above 6.0.

The DUPR system is believed to be an extension of the Elo system (Elo 1960) which was originally developed for chess. A feature of the DUPR system which is not a property of standard Elo is that DUPR takes margin of victory into consideration. For example, your updated DUPR rating will be greater if you win a match 11-4 than if you win a match 11-9. DUPR calculations also take the DUPR ratings of your opponents into account. Consequently, your DUPR rating is more affected (negatively) when you lose to weaker opponents.

Despite the long history associated with Elo and its solid theoretical underpinnings, this does not stop people from complaining about the DUPR system. A common complaint involves disappointment when a player's Elo rating goes down by more than a player expects. A problem with DUPR is that it is proprietary, and the exact formulae used in its calculations have not been revealed to the public. In future analytics work, it may be possible to improve on DUPR. It would be good to have a transparent system that is open to careful scrutiny.

5 DISCUSSION

We have reviewed recent activity in pickleball analytics and have contributed some new topics involving strategy (Section 2).

What is clear is that pickleball analytics requires data, and data collection is in its infancy. Data collection in pickleball is challenging due to the speed of the game. For example, a data collector would struggle recording aspects of successive shots in a "firefight". For example, it would be instructive to know shot details such as the location and the height of impact. Data is also useful for the estimation of probabilities (Section 2) when assessing strategies.

Even if games were recorded and could be watched slowly multiple times, data collection would still be challenging. What is needed in pickleball is advanced computer vision techniques that take film as input and produce workable data. This is what is being done in high level leagues in hockey, basketball and soccer. Until data collection is advanced, it will be difficult to make great headway in pickleball analytics.

Strategy is an important topic in pickleball analytics. Going forward, it is important to note that strategy is personal. What may be optimal for one player may not be optimal for another player. Future work involving strategy ought to consider relevant factors such as skill level in executing shots, athleticism, etc.

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