Original Research Article

Post-Touchdown Decision-Making in American Football: A Dynamic Programming Analysis of Extra Points and Two-Point Conversions

Simon Liu

Millburn High School, Millburn, New Jersey, United States

ABSTRACT

This paper uses nine years of National Football League (NFL) data to develop models that help teams decide whether to kick an extra point (XP) or attempt a two-point conversion after a touchdown. Two approaches are presented: a Possession-Neutral Model, which considers only the score and time left, and a Possession-Aware Model, which also accounts for possession. Both models use dynamic programming to estimate win probabilities in real time. The results suggest that possession meaningfully affects late-game win probability and that selected score margins can justify two-point attempts before the final moments of a game. The paper also reports important model assumptions, data processing rules, and sensitivity checks for the tie utility and score cap. The research provides data-backed guidance for in-game decision-making while identifying limitations that should be addressed in future work.

Keywords: Sports Analytics; American Football; Decision-Making; Dynamic Programming; Stochastic Modeling

INTRODUCTION

Using data and statistical models to analyze sports is nothing new. One major application is predicting winners for purposes such as sports betting, while another focus is on-field decisions aimed at improving performance and strategy. In modern athletics, both applications have become increasingly important.

NCAA (National Collegiate Athletic Association)-based studies, such as those analyzing March Madness tournaments in Kaplan and Garstka (1), and Kvam and Sokol (2), primarily focus on forecasting game outcomes and bracket results using probability models. These studies highlight how randomness and variability make accurate prediction difficult, particularly in single-elimination formats, where even strong teams face a significant chance of losing. While these works provide valuable insights into uncertainty and improving forecasting accuracy, they are largely limited to predicting results rather than influencing decision-making during games.

A notable example of sports analytics driving on-field performance is depicted in Michael Lewis's book Moneyball (3), which was later adapted into a widely known film. Both the book and the movie illustrate how the Oakland Athletics used data analysis to identify undervalued players and build a competitive team despite a limited budget. This approach marked a major shift in professional sports, showing that statistical reasoning could challenge traditional methods and significantly improve outcomes. Since then, analytics has expanded beyond baseball into other sports.

In American football, strategic decisions such as

Corresponding author: Simon Liu, E-mail: slapplelaser@gmail.com.

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fourth-down choices, play-calling, and post-touchdown conversion attempts can materially affect expected points and win probability. Prior work has shown that NFL coaching decisions often differ from strategies implied by expected-value or win-probability maximization. Romer (4), for example, used play-by-play data and dynamic programming to study fourth-down decisions and found systematic departures from choices that would maximize teams' chances of winning. Pelechrinis and Papalexakis (5) similarly documented conservative patterns in NFL coaching behavior across multiple decision types, including fourth-down attempts and point-after-touchdown choices. These studies provide evidence that NFL teams have historically exhibited conservative or risk-averse tendencies in selected high-leverage decisions, although the extent of such behavior depends on the decision context and era.

Using the last nine years of NFL play-by-play data, this paper develops an analytical model to determine whether a football team should attempt an extra point or go for a two-point conversion following a touchdown. The model employs dynamic programming to estimate in-game winning probabilities, in a manner similar to Asness and Brown (6), who investigated pulling the goalie in hockey. This paper develops two models for estimating the win probability at each time interval. The first, the Possession-Neutral Model, depends only on score differential and time remaining, ignoring which team is on offense or defense. The second, the Possession-Aware Model, builds separate value functions for offense and defense. Whether a two-point conversion is attempted then depends on which option provides a higher probability of winning. The purpose of the study is therefore not only to describe historical NFL coaching behavior, but also to evaluate when a value-based model would recommend a different post-touchdown decision.

METHODS AND MATERIALS

Data Processing and Reproducibility

The dataset was filtered to include NFL regular-season and playoff plays from 2017 through the portion of the 2025 season available at the time of analysis. Overtime plays were excluded because overtime rules can end a game immediately after a touchdown, making post-touchdown values different from regulation-time values. Each record was screened for a valid game identifier, game clock, scoring event, and drive identifier. Plays with incomplete time stamps or missing scoring labels were excluded from the event-count calculations. Duplicate records were identified by game identifier, quarter, game clock, play description, and scoring outcome, and exact duplicates were counted only once. Inconsistent labels for extra points, two-point tries, field goals, and touchdowns were mapped to common event categories before averages were computed. Safeties, defensive two-point returns, and defensive touchdowns were recorded as limitations but omitted from the baseline scoring recursion because they were rare and would require a richer turnover-state model. These preprocessing rules allow the parameter estimates in the Results section to be reproduced directly from the play-by-play file.

Possession-Neutral Model

The Possession-Neutral Model assumes that the winning probability of a team only depends on the score differential and time remaining. In this model, the progression of a football game is treated as a series of discrete time intervals. Specifically, the standard 60-minute game is divided into 360 individual periods, with each period representing 10 seconds of game clock. In this framework, the state of the game at any given moment is defined by two primary variables: the current score margin (x) and the time (t,). This model operates on the assumption of scoring symmetry, meaning that both teams have an equal probability of scoring during any 10-second interval. The scoring dynamics account for the most common ways a team's score can change:

- an 8-point outcome (touchdown plus two-point conversion),
- a 7-point outcome (touchdown plus extra point),
- a 6-point outcome (unsuccessful conversion),
- or a 3-point field goal.

Rare cases of scoring a safety are ignored to simplify the analysis. These are represented by the probabilities p_8, p_7, p_6, and p_3 respectively.

$$P[x_{t+1} = x_t + 8] = P[x_{t+1} = x_t - 8] = p_8$$

$$P[x_{t+1} = x_t + 7] = P[x_{t+1} = x_t - 7] = p_7$$

$$P[x_{t+1} = x_t + 6] = P[x_{t+1} = x_t - 6] = p_6$$

$$P[x_{t+1} = x_t + 3] = P[x_{t+1} = x_t - 3] = p_3$$

The probability of no change in score differential during a time step is defined as:

$$P[x_{t+1} = x_t] = p_0 = 1 - 2(p_8 + p_7 + p_6 + p_3)$$

To determine the optimal strategy, a Value Function Recursion is implemented that calculates the probability of winning, $V_t(x)$, at any specific score and time. At the end of the game ($T = 360$), the game result is known, so the value function of a win ($x > 0$) is 1, and the value of a loss is 0.

$$V_T(x) = \begin{cases} 1 & x > 0 \\ 0.6 & x = 0 \\ 0 & x < 0 \end{cases}$$

The assignment of a value of 0.6 rather than 0.5 to a tied game is a modeling assumption rather than an empirically estimated overtime win probability. The assignment of 0.6 to a tied game is intentional because it reflects the "utility of a tie." Imagine a team that just scored a touchdown and faces a one point deficit with no time remaining. Most teams would be risk-averse and opt for kicking an extra point to send the game to overtime rather than attempting a two-point conversion which has a high risk of losing the game immediately.

At any time t during the game ($0 < t < 360$), the score margin is capped at a range of [-50, 50]. Margins outside that range are treated as practical wins or losses because the estimated value functions are already extremely close to 1 or 0. A sensitivity check using ±40 and ±60 point caps produced the same number of two-point recommendations in the displayed score range, suggesting that the baseline ±50 cap does not drive the reported results.

$$V_t(x) = 1,\ \text{if } x \geq 50,\quad V_t(x) = 0,\ \text{if } x \leq -50.$$

This iterative process is employed to compute the win probability backwards from end of the game time (T) to the start time of the game (0). This involves summing the win probabilities of all possible future states, weighted by the likelihood of those scoring events occurring:

$$\begin{aligned} V_t(x) = {} & p_8 V_{t+1}(x+8) + p_7 V_{t+1}(x+7) + p_6 V_{t+1}(x+6) \\ & + p_3 V_{t+1}(x+3) + p_8 V_{t+1}(x-8) + p_7 V_{t+1}(x-7) \\ & + p_6 V_{t+1}(x-6) + p_3 V_{t+1}(x-3) + p_0 V_{t+1}(x) \end{aligned}$$

The probabilities are estimated using the last nine years of NFL play-by-play data (2017-2025) downloaded from Kaggle (6). In particular, the average number of touchdowns, successful two-point conversions, made extra points, failed conversions, made field goals, and drives per game are computed after applying the preprocessing rules described above. The empirical model treats these probabilities as constant across teams, seasons, field position, and game context; this simplifying assumption improves transparency but limits individual-game precision.

The probability of scoring a field goal (3 points) by any one team in a 10 second time step is

$$p_3 = \frac{1}{2}\,\frac{\#\,\text{Field Goals}}{360}$$

Likewise, the probability of scoring a touchdown plus two-point conversion, or touchdown plus extra point are

$$p_8 = \frac{1}{2}\,\frac{\#\,\text{Two Points}}{360},\quad p_7 = \frac{1}{2}\,\frac{\#\,\text{Extra Points}}{360}$$

Ignoring the rare no-try case for touchdowns, the probability of scoring a touchdown but failing the extra point or two-point conversion is

$$p_6 = \frac{1}{2}\,\frac{\#\,\text{Touchdowns}}{360} - p_8 - p_7$$

The model also uses the average number of extra point attempts and extra points earned, as well as the average number of two-point attempts and two points earned in a game to estimate the success rate of an extra point (r_1) and two-point conversion (r_2).

Once the full value matrix for the function $V_t(x)$ is computed, the optimal conversion decision can be made. After a touchdown at time t, the score differential is updated to x, and then team win probability of going for extra point or two-point conversion is given by

$$V(\text{Extra Point}) = r_1 V_t(x+1) + (1 - r_1) V_t(x)$$

$$V(\text{Two Points}) = r_2 V_t(x+2) + (1 - r_2) V_t(x)$$

The two-point conversion is chosen when $V(\text{Two Points}) \geq V(\text{Extra Point})$.

Possession-Aware Model

The second model introduces a higher level of complexity by distinguishing between whether a team is on offense or defense. In this model, the probability of winning depends on the score differential (x), time (t), and possession state (O or D). The value functions for the two possession types are built separately, $V_t^O(x)$ and $V_t^D(x)$. This is a more realistic reflection of football, where scoring usually occurs when a team possesses the ball. The model still excludes defensive scoring, safeties, and defensive returns on conversion attempts; these exclusions simplify the recursion but understate the small probability that a team on defense can score or that a conversion attempt can create points for the opponent.

The value functions at the end of the game,

$$V_T^O(x) = V_T^D(x) = \begin{cases} 1 & x > 0 \\ 0.6 & x = 0 \\ 0 & x < 0 \end{cases}$$

and at any time period t during the game ($0<t<T$), when the score differential is more than 50,

$$V_t^O(x) = V_t^D(x) = 1, \textit{ if } x \geq 50,$$

$$V_t^O(x) = V_t^D(x) = 0, \textit{ if } x \leq -50,$$

To link these states together, a possession persistence variable, q, is introduced. It represents the probability that the team currently on offense will remain on offense in the next 10-second interval. Conversely, $1 - q$ represents the probability of change in possession, either due to scoring, punt, or a turnover. When on offense, the model accounts for the team scoring and subsequently moving to a defensive state, as scoring a touchdown or field goal usually results in kicking the ball back to the opponent. The iterative equation for the offensive win probability is:

$$\begin{aligned} V_t^O(x) &= p_8 V_{t+1}^D(x+8) + p_7 V_{t+1}^D(x+7) + p_6 V_{t+1}^D(x+6) \\ &\quad + p_3 V_{t+1}^D(x+3) + (1 - q - p_3 - p_6 - p_7 - p_8)\, V_{t+1}^D(x) \\ &\quad + q\, V_{t+1}^O(x) \end{aligned}$$

The defensive recursion, $V_t^D(x)$, mirrors this logic but focuses on the opponent's scoring potential and the team's hope of regaining possession.

$$\begin{aligned} V_t^D(x) &= p_8 V_{t+1}^O(x-8) + p_7 V_{t+1}^O(x-7) + p_6 V_{t+1}^O(x-6) \\ &\quad + p_3 V_{t+1}^O(x-3) + (1 - q - p_3 - p_6 - p_7 - p_8)\, V_{t+1}^O(x) \\ &\quad + q\, V_{t+1}^D(x) \end{aligned}$$

In the Possession-Aware Model, the estimated scoring probabilities are effectively doubled during offensive possessions, compared with the Possession-Neutral Model, to reflect that a team generally cannot score while on defense.

$$p_3 = \frac{\#\,\textit{Field Goals}}{360},\ p_8 = \frac{\#\,\textit{Two Points}}{360},$$

$$p_7 = \frac{\#\,\textit{Extra Points}}{360},\ p_6 = \frac{\#\,\textit{Touchdowns}}{360} - p_8 - p_7\,.$$

The possession persistence probability q is estimated from the average number of drives in a game. The average duration (d) of one drive in terms of number of 10-second time steps satisfies

$$d = \frac{360}{\#\,\textit{Drives}} = (1-q) + 2q\,(1-q) + 3q^2\,(1-q) + \ldots,$$

therefore,

$$q = 1 - \frac{1}{d} = 1 - \frac{\#\,\textit{Drives}}{360}$$

Immediately following a touchdown, the model calculates the preference for a two-point try by comparing the expected win probability of a successful extra point against the two-point attempt:

$$V\,(\textit{Extra Point}) = r_1 V_t^D(x+1) + (1-r_1)\, V_t^D(x)$$

$$V\,(\textit{Two Points}) = r_2 V_t^D(x+2) + (1-r_2)\, V_t^D(x)$$

The two-point conversion is chosen when V (*Two Points*) $\geq V$ (*Extra Point*). Both dynamic programming recursions were implemented using Python.

RESULTS

The NFL games dataset was obtained from NFL Game Data: Scores & Plays on Kaggle (7). This analysis across nine years (2017-2025) of regulation-time play-by-play records from 2,635 regular-season and playoff games yielded the frequency and success rates of scoring events and drives. Python scripts parsed scoring plays, conversion attempts, and drive identifiers; records with missing scoring fields, incomplete clocks, or duplicated play descriptions were removed from the event counts. The completeness and high quality of the database ensured a straightforward process, requiring little data cleaning. Across the analyzed games, the following league-wide averages were determined:

- Average Touchdowns (TD) per Game: 5.09
- Average Extra Point (XP) Attempts per Game: 4.58
- Average Extra Point Made per Game: 4.31

- Average 2-Point Conversion (2PT) Attempts per Game: 0.51
- Average 2-Point Conversion Made per Game: 0.24
- Average Field Goals per Game: 3.4
- Average Drives per Game: 22.06

These per-game averages, including the possession persistence probability q, are converted into 10-second interval probabilities by dividing the occurrences by 360 (the number of time steps in a standard game). For the Possession-Neutral Model, these values are halved to reflect the probability of either team scoring. The resulting parameters used in the recursion are:

Model Parameter	Possession-Aware Model	Possession-Neutral Model
p_8 (TD + successful 2PT)	0.000667	0.000333
p_7 (TD + successful XP)	0.011972	0.005986
p_6 (TD + failed conversion)	0.001500	0.000750
p_3 (Field Goal)	0.009444	0.004722
q (Possession Persistence)	0.938722	–
r_1 (Extra Point Success Rate)[1]	0.941048	
r_2 (2-Point Conversion Success Rate)	0.470588	

Note: q is blank for the Possession-Neutral Model because that model does not include possession states. The XP success rate (r_1) and two-point conversion success rate (r_2) are shared by both models because they are estimated from the same league-wide conversion-attempt data.
[1]Extra Point Success Rate and 2-Point Conversion Success Rate are the same for the two models.

As an example, the value functions are analyzed at time step , representing roughly one minute and 40 seconds remaining in regulation. At this late stage, the win probability becomes highly sensitive to the score differential.

In the Possession-Neutral Model, the win probability follows a singular trajectory based purely on the score margin. As shown in Figure 1, the value function exhibits a sharp increase around the tie-game threshold ($x = 0$), where the assigned utility of 0.6 for a tie creates a strategic "anchor" for teams facing a deficit.

The Possession-Aware Model introduces a divergence between the offensive (blue) and defensive (green) states (Figure 2). Because scoring is concentrated during offensive possessions, the model recognizes that holding the ball late in the game significantly increases a team's win probability at almost every score margin. Conversely, a team on defense with a narrow lead faces a steeper drop in win probability compared to the neutral model, as they lack the immediate agency to run out the clock or extend the lead through scoring. It is also consistent with modern football analytics frameworks in which win probability is estimated from game-state variables such as score, time remaining, field position, down, distance, timeouts, and possession-related information (8).

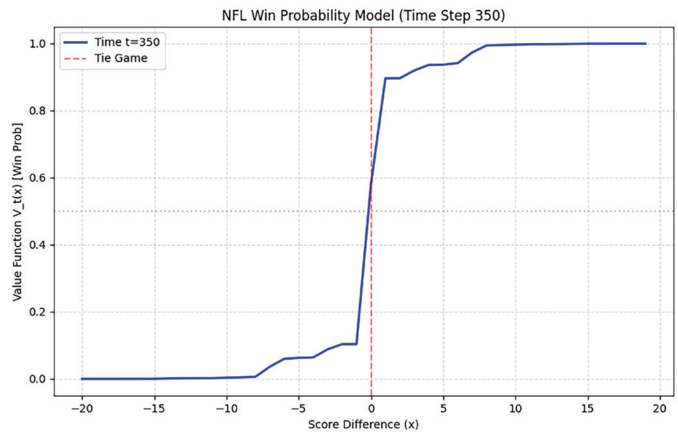

Figure 1. *Possession-Neutral Model: Value functions (win probabilities) at time step 350. The x-axis represents the score difference (x = 0 represents a tied game). The y-axis represents the win probability of a team given the score difference at time step 350 (1 minute 40 seconds remaining in the 4th quarter).*

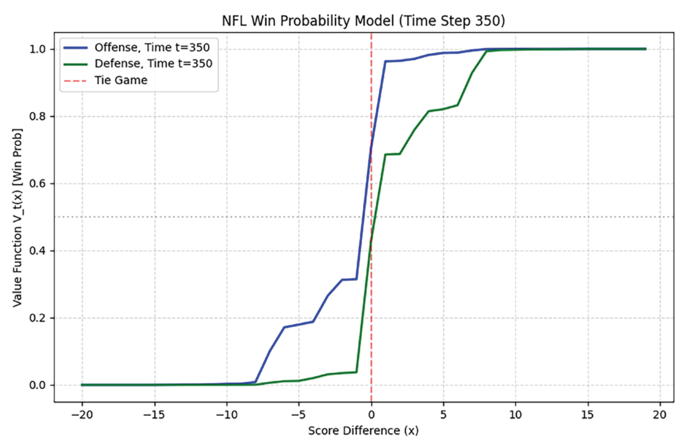

Figure 2. *Possession-Aware Model: Value functions (win probabilities) at time step 350. The x-axis represents the score difference (x = 0 represents a tied game). The y-axis represents the win probability of both offensive and defensive teams given the score difference at time step 350 (1 minute 40 seconds remaining in the 4th quarter). The blue line represents the win probability of the team that is currently on offense. The green line represents the win probability of a team that is currently on defense.*

Because the Possession-Aware Model accounts for which team has the ball, it is more informative for post-touchdown decision-making than the Possession-Neutral Model. The neutral model is useful as a transparent baseline and shows how score and time alone influence win probability. The possession-aware model adds an important state variable and therefore changes the value of being tied, ahead, or behind late in the game. For this reason, the remaining analysis in this paper focuses on the Possession-Aware Model.

DISCUSSION

The practical application of the Possession-Aware Model for deriving the optimal conversion strategy is illustrated in Figure 3. By comparing the expected values of a one-point kick and a two-point attempt, the figure maps the mathematically optimal decision across different score margins at t = 350. The results show that when the score is tied immediately after a touchdown and before the conversion attempt (x = 0), the model recommends kicking the extra point to obtain a one-point lead. This outcome is intuitive: both the one-point and two-point options result in a lead, but the extra point carries a substantially higher probability of success. Moreover, if the opponent were to score a field goal or a touchdown within the remaining one minute and forty seconds, neither choice would be sufficient to secure the lead, making the safer option optimal. Similar trade-offs between success probability and strategic value arise across other score margins, and the model's recommendations reflect these underlying considerations.

To further illustrate that the implications of the model framework are not limited to late-game situations, Figure 4 displays value functions and optimal decision mappings at (20 minutes remaining). Figure 4(B) shows that even with substantial time left on the clock, the Possession-Aware Model already identifies score margins where attempting a two-point conversion dominates the conventional extra point kick in terms of expected value. Importantly, this recommendation emerges well before the endgame, indicating that optimal risk-taking is not merely a response to desperation or limited remaining possessions, but rather a forward-looking adjustment to how future possessions are likely to unfold. This result should be interpreted as a model-generated finding rather than as an established empirical fact. It contrasts with observed NFL practice in which two-point attempts occur disproportionately late in games. Auman (9) reports that 72% of NFL two-point attempts in the referenced season occurred in the fourth quarter. The model therefore suggests that, under its assumptions and league-average conversion rates, some earlier two-point attempts may increase estimated win probability and preserve more favorable score combinations for later possessions.

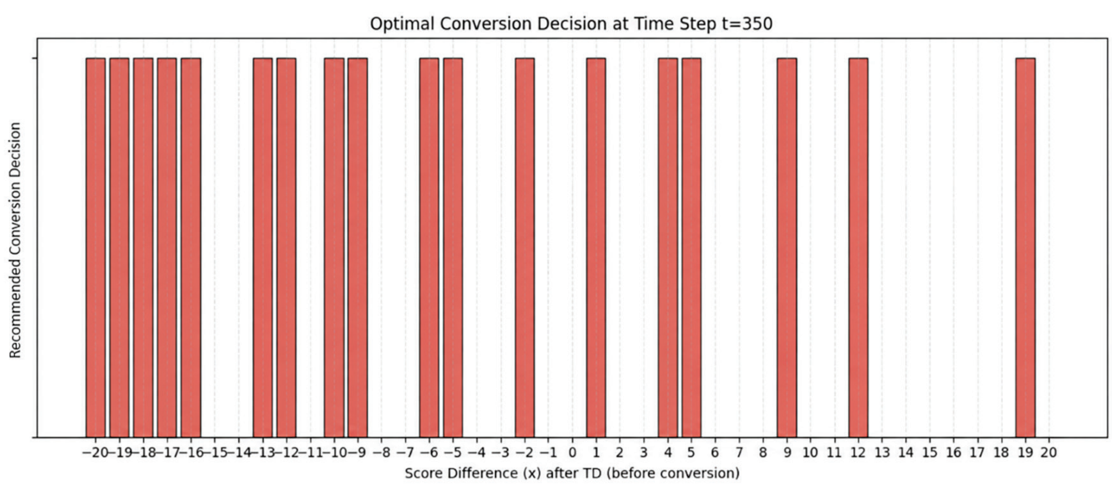

Figure 3. *Possession-Aware Model: Optimal conversion decisions at time step 350. The x-axis represents the score difference after a touchdown but before the XP or two-point conversion. The y-axis categories show the model's recommended post-touchdown strategy: Red bars identify score differences where the model recommends going for two; blank spaces identify score differences where the model recommends kicking the XP.*

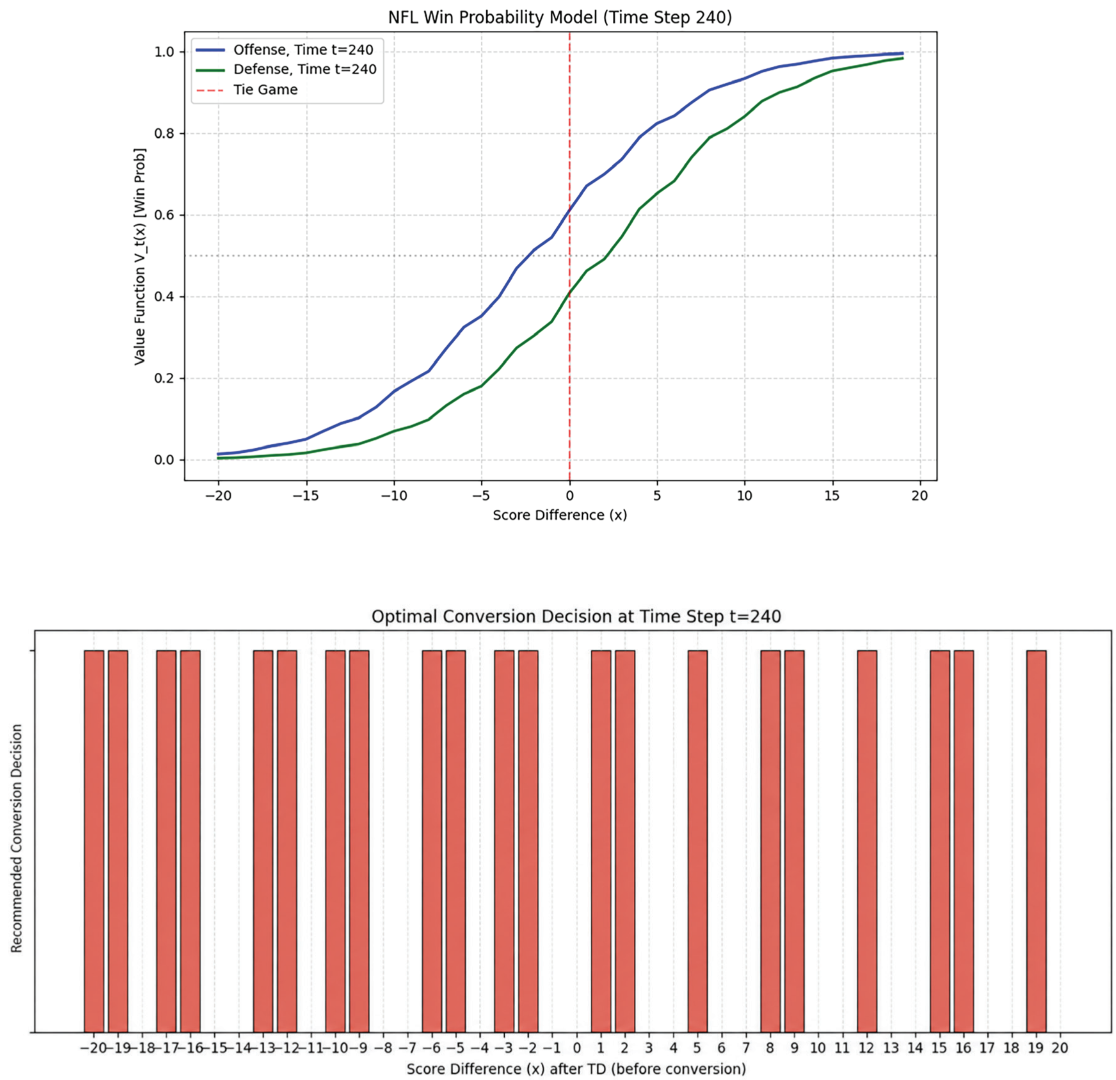

Figure 4. *Possession-Aware Model at time step 240. (A) Estimated offensive and defensive win probabilities by score differential. (B) Recommended post-touchdown conversion decision by score differential; red bars indicate a two-point attempt, whereas blank positions indicate an extra-point attempt.*

The non-smooth appearance of the value functions follows directly from the discrete scoring structure of American football. Under NFL scoring rules, the most common scoring increments are 3 points for a field goal, 6 points for a touchdown, 1 point for a kicked try after touchdown, and 2 points for a two-point try (10). These scoring increments create a value function that is naturally jagged, and is why the model frequently suggests going for a two-point conversion despite being far from the end of the game. The points at which the model recommends attempting a two-point conversion can be identified from their mathematical properties. When the function is locally convex, a team can gain a disproportionately large increase in win probability by shifting the score margin to the right. And so, the model takes on more risk, calculating that the value of gaining two points outweighs the safer option of an extra point. The opposite can therefore be said when the curve is locally concave.

A clear example of these models producing different and potentially better decisions comes from the 2025-2026 NFC (National Football Conference) Championship

Game between the Seattle Seahawks and Los Angeles Rams. The Rams scored a touchdown with 9 minutes and 41 seconds left in the third-quarter to make the score 19-24 (5 points behind Seahawks), the model recommends that the Rams attempt a two-point conversion, but they instead chose the safer extra point, narrowing the score to 20-24. Later in the same quarter with 2 minutes and 6 seconds left, the Rams scored again to make it 26-31. In this case, the model also recommends the two-point conversion, but once again the Rams opted for an extra point rather than going for two, bringing the score to 27-31. These cautious choices had important consequences late in the game. With the score still being 27-31 in the fourth quarter, the Rams needed a touchdown and were forced into a high-pressure fourth-down attempt at the goal line, since a field goal would not have been enough. The attempt failed, effectively ending their chances. Notably, even if the Rams had failed both earlier two-point attempts, the score would have been 25-31, a six-point gap, meaning they still would have needed a touchdown. While it is easier to evaluate these decisions in hindsight, this example highlights how the model's recommendations could have improved the team's strategic flexibility and win probability.

CONCLUSION

This research connects sports analytics with in-game decision-making by creating a mathematical framework for one of the NFL's most common strategic choices. While many studies focus on predicting outcomes after games or analyzing general coaching trends, this paper uses dynamic programming and nine years of play-by-play data to produce real-time win-probability estimates. By comparing a Possession-Neutral baseline with a Possession-Aware model, the analysis shows how possession, score difference, and time remaining interact in post-touchdown decisions.

The findings suggest that the extra point is not always the value-maximizing choice. At selected score margins, the Possession-Aware Model recommends a two-point attempt because the additional point has enough strategic value to offset the lower conversion rate. By successfully creating a strong value-based model, this study offers a clear guide for making smarter decisions. In the end, it shows that when teams base their choices on data instead of habit, they can improve their chances of winning.

While this study provides a strategic framework for the point-after-touchdown decision, a limitation is that scoring probabilities were estimated from current data; if this model were adopted by one or both teams, it would likely alter the frequency of 2-point attempts and the resulting probabilities of winning 7 or 8 points. Furthermore, the value function in the model simplifies the game state by assuming the defense cannot score, thereby excluding "points off turnovers" such as defensive returns on fumbles or interceptions. Future research should aim to refine this model by accounting for the impact of the model decisions on the probabilities of different scoring outcomes and incorporating defensive scoring. Beyond the scope of 2-point conversions, this framework could be extended to more complex scenarios, such as fourth-down attempts, in future research. This would require the integration of additional contextual variables such as field position to fully reflect the complicated nature of real-time football strategy.

CONFLICT OF INTEREST

The author declares no conflicts of interest related to this work.

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