**Impact of the Pitch Clock on Pitching Strategies (2021–2024)**

Focusing on the Tampa Bay Rays

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Introduction: The Impact of the MLB Pitch Clock—A Broad Overview and Deeper Insights

The introduction of the pitch clock in Major League Baseball (MLB) on March 30, 2023, has transformed the game’s pace and overall dynamics, as reported by the Wall Street Journal. Designed to accelerate play and enhance the fan experience, this rule mandates pitchers to deliver within 15 seconds (no runners on base) or 20 seconds (runners on base), yielding measurable changes across the league. Our analysis leverages play-by-play data from Tampa Bay Rays (TBA) home games against AL East opponents (BAL, BOS, NYY, TOR) across the 2021–2024 seasons to explore these shifts, focusing on pitch sequences, types, and situational adjustments.

* Reduction in Game Duration: In its inaugural year, the pitch clock reduced the average time of a nine-inning MLB game to 2 hours and 40 minutes, a notable 24-minute decrease from previous seasons, according to ESPN. This efficiency aligns with MLB’s goal to maintain competitiveness in a fast-paced entertainment landscape.
* Impact on Gameplay: While the clock has shortened games, core statistical trends remain stable. Batting averages continue to decline, and strikeout rates have risen, suggesting that the style of play—dominated by pitchers—has not shifted dramatically. The pitch clock’s primary effect appears to be on timing rather than altering the fundamental pitcher-batter duel.
* Fan Engagement and Attendance: The quicker pace has revitalized fan interest. In 2024, MLB experienced a resurgence in popularity, with playoff viewership surging by nearly 20% and regular-season attendance reaching its highest level since 2017, as noted by the Wall Street Journal. This boost highlights the pitch clock’s success in enhancing the spectator experience.

In summary, MLB’s pitch clock has achieved its objectives of reducing game times and boosting fan engagement, even as on-field trends like strikeouts persist. Many analyses, including those on informational websites and news outlets, often conclude here, celebrating these surface-level wins. However, the story doesn’t end with game times and attendance figures—there’s a deeper layer to uncover. Borrowing a phrase from the legendary radio host Paul Harvey, let’s explore the “Rest of the Story” by delving into how the pitch clock is reshaping pitchers’ strategies and pitch selections, illuminated by our data-driven study of Rays pitchers from 2021 to 2024.

Methodology

We extracted pitch sequence data from the play\_by\_play table, focusing on Rays starting pitchers facing AL East teams (BAL, BOS, NYY, TOR) across the 2021–2024 seasons. The dataset was split into Pre-Clock (2021 and pre-March 30, 2023) and Post-Clock (post-March 30, 2023, including 2024) periods, yielding 510 samples (278 Pre-Clock, 232 Post-Clock), a significant increase from the initial 258 samples from 2022–2023. Key features included pitch steps (e.g., B for ball, F for fastball), sequence length, balls, strikes, and encoded pitcher and batter identities. An XGBoost model was trained to predict the clock period (Pre- vs. Post-Clock) based on these features, achieving a test accuracy of 0.93 and a cross-validation F1-macro score of 0.93 ± 0.02. Feature importance analysis and pitcher-specific breakdowns were used to identify changes in pitching strategies over the four-year period.

Findings: How the Pitch Clock is Changing Pitching Strategies

The pitch clock has introduced notable shifts in pitching behavior, as evidenced by our expanded analysis:

1. Pitcher-Specific Adaptations Drive Changes:
   * The most significant predictor of clock period was pitcher\_encoded (feature importance: 0.601), indicating that individual pitcher strategies heavily influence adaptations to the pitch clock. This suggests that pitchers vary widely in how they adjust to time constraints, likely based on their pitching style, experience, or comfort with the new rules.
   * For example, pitchers like Shane McClanahan (mccls003), Ryan Yarbrough (yarbr001), Tyler Glasnow (glast001), and Shawn Armstrong (armss001) showed distinct sequence patterns pre- and post-clock, as detailed below.
2. Increased Reliance on Fastballs:
   * The pitch type F (fastball, feature importance: 0.048) remained a key differentiator, suggesting pitchers are more likely to throw fastballs under the clock’s time pressure. Fastballs, being quicker to deliver than off-speed pitches, align with the need to meet the 15/20-second limit, reducing the risk of violations.
   * This trend supports anecdotal evidence that pitchers simplify their approach to maintain rhythm, especially in high-pressure situations (e.g., against batters like Aaron Judge—judga001—where Taj Bradley (alext001) used FBBS.BX sequences in inning 1).
3. Shorter Pitch Sequences:
   * sequence\_length (feature importance: 0.043) indicates that pitch sequences tend to be shorter post-clock. The time constraint discourages drawn-out at-bats with multiple foul balls or takes, pushing pitchers to work more efficiently. For instance, Bradley’s sequences against cleme002 (inning 1) included BCFX, reflecting a decisive approach.
4. Situational Adjustments:
   * Features like balls (0.042) and strikes (0.036) show that situational context matters. Pitchers are more cautious with balls early in the count to avoid walks (which reset the clock), but they’re also quicker to throw strikes to expedite at-bats.
   * The balls\_strikes\_interaction (0.047) suggests that in high-pressure counts (e.g., 3-2), pitchers may rush to deliver strikes, sometimes at the expense of control, as seen in Bradley’s BBC.CFB>C against kirka001 (inning 1).
5. Batter Matchup Dynamics:
   * batter\_encoded (0.070) highlights the role of pitcher-batter matchups. Pitchers adjust strategies based on the batter’s tendencies under the clock, especially against power hitters like Aaron Judge (judga001), where quick, decisive pitches (e.g., FBBS.BX) are favored to minimize prolonged at-bats.
   * Outcomes (X, 0.052) and strikes (S, 0.061) also increased in importance, suggesting that balls in play and strikeouts are more frequent post-clock, possibly due to rushed pitches or more aggressive strategies.

Pitcher-Specific Adaptations: Case Studies

Using pitcher-specific pitch step frequencies across 2021–2024, we identified how individual Rays pitchers adapted to the pitch clock:

* Shane McClanahan (mccls003):
  + Pre-Clock (306 sequences): McClanahan’s pitch steps were {'B': 366, 'S': 194, 'X': 194, 'C': 187, 'F': 149}, averaging 0.49 fastballs per sequence (F: 149/306).
  + Post-Clock (67 sequences): His pitch steps shifted to {'B': 83, 'F': 54, 'S': 49, 'X': 38, 'C': 35}, with fastballs increasing to 0.81 per sequence (F: 54/67). This 65% increase in fastball frequency suggests McClanahan relied more heavily on fastballs to meet the clock’s time constraints, likely to maintain control and rhythm under pressure.
  + Sequence Count Decrease: The drop from 306 to 67 sequences may reflect fewer starts (e.g., due to injury in 2023–2024), but the proportional increase in fastballs aligns with the broader trend of simplifying pitch selection.
* Ryan Yarbrough (yarbr001):
  + Pre-Clock (174 sequences): Yarbrough’s pitch steps were {'B': 228, 'C': 127, 'F': 126, 'X': 125, 'S': 72}, averaging 0.72 fastballs per sequence (F: 126/174).
  + Post-Clock (15 sequences in subset): His pitch steps shifted to {'B': 16, 'F': 12, 'C': 10, 'X': 9, 'S': 6}, averaging 0.80 fastballs per sequence (F: 12/15). This 11% increase in fastball frequency indicates a slight shift toward quicker pitches, though Yarbrough’s smaller post-clock sample suggests limited usage (possibly due to trades or role changes in 2023–2024).
* Tyler Glasnow (glast001):
  + Pre-Clock (26 sequences): Glasnow’s pitch steps were {'B': 32, 'C': 19, 'F': 14, 'X': 14, 'S': 13}, averaging 0.54 fastballs per sequence (F: 14/26).
  + Post-Clock (118 sequences): His pitch steps shifted to {'B': 173, 'C': 85, 'F': 80, 'S': 72, 'X': 64}, averaging 0.68 fastballs per sequence (F: 80/118). This 26% increase in fastball frequency suggests Glasnow adapted well, maintaining a high volume of pitches (118 sequences) with a focus on quicker deliveries under the clock.
* Shawn Armstrong (armss001):
  + Pre-Clock (11 sequences): Armstrong’s pitch steps were {'B': 13, 'X': 8, 'F': 8, 'S': 7, 'C': 2}, averaging 0.73 fastballs per sequence (F: 8/11).
  + Post-Clock (7 sequences): His pitch steps shifted to {'B': 12, 'F': 7, 'X': 4, 'S': 3, 'C': 2}, averaging 1.0 fastballs per sequence (F: 7/7). This 37% increase, though on a small sample, indicates Armstrong leaned heavily on fastballs post-clock, possibly to expedite at-bats against hitters like Aaron Judge (judga001, BX in inning 1).

Model Performance and Limitations

The XGBoost model achieved a test accuracy of 0.93, with balanced F1 scores (0.94 Pre-Clock, 0.92 Post-Clock), indicating strong predictive power. To assess generalization, we used a repeated 5-fold cross-validation (5 repeats, 25 total folds), yielding an F1-macro score of 0.93 ± 0.02. Here’s what these metrics mean:

* Test Accuracy of 0.93:
  + Test accuracy measures the proportion of correct predictions on a held-out test set (20% of the data, 102 samples out of 510). An accuracy of 0.93 means the model correctly classified 93% of sequences as Pre- or Post-Clock, such as identifying whether Taj Bradley’s FBBS.BX sequence against Aaron Judge (judga001) occurred before or after the pitch clock’s introduction. In a binary classification problem (Pre-Clock vs. Post-Clock), a random guess would yield an accuracy of 0.50, so our 0.93 accuracy demonstrates the model’s ability to capture meaningful patterns, such as increased fastball usage (F) or shorter sequences post-clock.
* Cross-Validation F1-Macro Score of 0.93 ± 0.02:
  + Cross-Validation: We used repeated 5-fold cross-validation (5 repeats, 25 folds total), dividing our 510 samples into 5 folds of approximately 102 samples each, repeating the process 5 times with different splits. This approach ensures a robust estimate of performance by testing the model on multiple subsets of the data, reducing the risk of overfitting to a single train-test split.
  + F1-Macro Score: The F1-score balances precision (how many predicted positives are correct) and recall (how many actual positives are correctly predicted). For binary classification, we compute the F1-score for each class (Pre-Clock and Post-Clock) and take the unweighted average—the F1-macro score. This treats both classes equally, despite their slight imbalance (278 Pre-Clock, 232 Post-Clock), ensuring the model isn’t biased toward the majority class. An F1-macro score of 0.93 means that, on average across the 25 folds, the model achieved a balanced performance of 0.93 (on a scale from 0 to 1) for both Pre- and Post-Clock classes.
  + Variability of ±0.02: The ±0.02 indicates the range of F1-macro scores across the folds, calculated as twice the standard deviation of the 25 fold scores. A mean of 0.93 with ±0.02 means the F1-macro scores ranged from approximately 0.91 to 0.95, showing exceptional consistency in the model’s performance. This tight variance, improved from the previous 0.91 ± 0.03 with 258 samples, reflects the benefit of a larger dataset (510 samples), repeated cross-validation, and model regularization (e.g., max\_depth=3).
  + Interpretation: The CV F1-macro score of 0.93 ± 0.02, closely aligned with the test accuracy of 0.93, indicates the model generalizes exceptionally well, with consistent performance across different data splits. This high score gives confidence that the model can reliably identify clock-induced changes in pitching behavior when applied to new data, such as future seasons or different teams.

The expanded dataset (510 samples) has improved the model’s robustness, as evidenced by the tighter cross-validation variance and higher accuracy. However, potential limitations remain if pitching behaviors vary significantly across seasons or teams not included in this analysis (e.g., non-AL East opponents. This report was specifically encoded for the AL East in regards to Tampa Bay pitchers ). Future work will further expand the dataset to include all MLB teams or additional game contexts (e.g., inning, outs) to enhance generalizability.

Conclusion

The pitch clock has significantly altered pitching strategies for Rays starters against AL East opponents over the 2021–2024 seasons. Pitchers are adapting by relying more on fastballs, shortening their sequences, and adjusting based on individual tendencies and situational factors. The dominance of pitcher-specific effects (pitcher\_encoded, 0.601) underscores the need for personalized analysis—some pitchers, like Shane McClanahan (65% fastball increase) and Shawn Armstrong (37% increase), thrive under the clock by increasing fastball usage, while others, like Ryan Yarbrough (11% increase), show more modest adjustments, possibly due to limited post-clock usage. Tyler Glasnow’s 26% fastball increase and high sequence volume (118) suggest successful adaptation. The model’s high accuracy (0.93) and robust cross-validation (0.93 ± 0.02) provide strong confidence in these findings, demonstrating reliable identification of clock-induced trends across the expanded dataset. Future works will show additional contextual factors and broader team coverage to ensure comprehensive insights into pitch clock impacts across MLB.