Powerful Metrics: The Overlooked Factor Behind Softball Pitch Speed

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Speed is essential to the success of softball pitchers. Despite working on traditional pitching performance metrics, the pitchers at Planet Fastpitch (PFP), an elite softball training facility in Massachusetts, did not achieve the desired increase in speed. What should these athletes focus on? The primary hypothesis was that strength plays a significant role in pitch speed, in addition to or more than traditional mechanics. To explore this, metrics of strength (e.g., grip strength) and kinematic performance (e.g., stride length) were collected from 45 athletes in the spring of 2025. The data were analyzed with multivariate linear regressions and produced a statistically strong three-variable model explaining 58% of speed variation with an adjusted R^2 of 0.55, with each variable's p-value < 0.05. Importantly, the results confirmed the hypothesis, as this model outperformed the single variable performance only model, showing that strength notably enhances the model's predictive performance. In addition to pitch speed, we considered batter reaction time, the time the hitter has from when the ball leaves the pitcher's hand to when it reaches the plate. We discovered that while strength remains important, the coefficient for the performance metrics switched sign, suggesting that the direction of impact flipped. Together, these novel and actionable findings identify strength as a major contributor to pitch speed and clarify how the relevance of each metric changes depending on the predicted variable. The results provide suggestions for pitchers' training, coaching, and future research.

Keywords: Softball, Pitching, Strength, High School Athletics, Multi-variable Linear Regression, Softball Mechanics, Pitch Speed, Reaction Time

Introduction

In softball, pitch speed can change games and often defines a pitcher's success. While pitchers may therefore be highly motivated to improve their speed, there are numerous aspects and metrics on which they could focus. This study aimed to determine the best model of measurable attributes to predict the speed of a softball pitch. To better understand this question, we sought to develop a model that predicts the speed of a softball pitch.

Prior research has examined fastpitch softball windmill pitching and throwing in general, identifying biomechanical and strength-related factors. Researchers have studied the biomechanics of softball pitching in considerable detail and have broken the softball windmill pitching motion into distinct phases[1–4]. Most relevant to this paper, research has examined the relationship between pitching form and pitch speed. For example, Oliver et al. also evaluated multiple mechanical variables and found moderate correlations with pitch speed, with an average r of 0.51 ($R^2 \approx 0.27$)[3]. Separately, considerable research has been conducted on the relationship between strength and overhand throw speed, as well as studies examining the relationship between pitching speed and strength in softball. Prior studies have focused on individual variables, but no work has compared the relative contributions of mechanics and strength within the same predictive framework for softball windmill pitching.

The aim of this study was to evaluate how mechanical performance metrics and strength-related measures jointly predict pitch speed. It was hypothesized that strength would contribute additional explanatory value beyond traditional performance variables. In this study, three types of metrics were considered, as detailed in Table 2 of the Methods section. Performance metrics are what pitchers typically seek to optimize as they are building their mechanics. Examples include lift to land (seconds), land to release (seconds), and stride length (feet). We also consider strength-related power metrics, including vertical jump, seated chest press, and grip strength. Finally, we considered inhibitors, which are actions during a pitch that slow down speed, such as losing space and anchoring. This data was collected from 45 high school-aged pitchers who train at the same facility.

To do this, we analyzed this dataset using linear modeling to assess how mechanical and strength-related metrics relate to pitch speed. We compared single and multivariable models to examine whether strength contributed information be-

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yond mechanical performance measures. This allowed us to assess whether strength provided additional explanatory value for this cohort of pitchers.

Related work

Researchers have studied the biomechanics of fastpitch softball pitching in considerable detail. Early studies described how the trunk, pelvis, shoulder, and elbow work together to create the angular velocities needed for the windmill motion. They established the basic timing patterns of the pitch[1–4]. More recent investigations have measured how factors such as stride length, trunk-rotation timing, hip mobility, and the transfer of energy from the lower body to the arm contribute to differences in pitch speed and mechanical efficiency across athletes at various levels[5,6]. Both Friesen and Milanovich et al. have outlined the windmill pitch in clearly defined phases, providing practical frameworks that can be used as reference points in these analyses[1,7].

Most relevant to this paper, research has examined the relationship between pitching form and pitch speed. Konz and Wheeler studied 14 Big XII college pitchers and, using single-variable regressions, reported that stride length and several other mechanics predicted ball velocity ($R^2 = 0.32$)[8]. Oliver et al. also evaluated multiple mechanical variables and found moderate correlations with pitch speed, with an average r of 0.51 ($R^2 \approx 0.27$)[3]. Similarly, Torres et al. identified a positive association between stride length and softball pitch speed, though with a smaller effect size ($R^2 = 0.115$)[9]. These studies only observed mechanics and did not include other variables such as strength or inhibitors.

There has been a lot of research on the relationship between strength and overhand throw speed. Much of this work focuses on sports other than softball; for example, McEvoy and Newton examined a baseball throw. Eighteen National League baseball players were split into two groups: one control group that performed no additional training and one that completed ballistic training, including explosive squat jumps and bench throws. Both groups continued their everyday practice routines, and the researchers found that the training group increased throwing speed by $2.0 \pm 1.5\%$ ($p \leq 0.05$), while the control group showed no change[10]. Ekaterini et al. conducted a similar intervention where one group trained with a lighter ball, another with weighted implements, and a third served as a control[11]. The two training groups improved from 18.2 ± 0.3 m/s to 20.2 ± 0.4 m/s ($p < 0.05$) and from 17.8 ± 0.4 m/s to 20.1 ± 0.4 m/s ($p < 0.05$), respectively, while the control group showed a smaller gain from 18.0 ± 0.4 m/s to 19.1 ± 0.3 m/s[12]. Other research also supports a strong link between strength or power training and gains in throwing performance. Wooden et al and Escamilla et al found over several studies that velocity improvements in teenage baseball players followed a structured strength-training program[13,14]. There have also been several studies that show grip strength is helpful for overhand throw[15–17]. For example, Ferragut et al. did a study on water polo players and found grip strength was correlated with overhand throw velocity ($R^2 \approx 0.364$, $P<0.05$)[18]. Lastly, more relevant to this study, a study by Razak et al. involving 72 college athletes showed that grip strength significantly increased overhand (non-pitching) softball throw velocity. They did not control for mechanics or form[19]. These studies only observed overhand throw, not windmill pitch.

Research has been conducted on the relationship between pitch speed and strength in softball. Pugh et al.'s experiment with 16 experienced pitchers and 16 inexperienced pitchers showed that grip strength was correlated with pitch speed for experienced pitchers[20]. Oliver et al. and Pletcher et al. studied the relationship between hip strength and speed, discovering that strong hips move energy throughout the kinetic chain, and cited studies showing that pitchers with greater energy flow tend to throw faster, suggesting that strength is also associated with speed[5,21]. These studies did not include mechanics.

Lastly, there has been research on the muscles used in a softball pitch. Remaley et al. examined how muscles, specifically the Flexor carpi ulnaris, are utilized differently during the throwing of various pitches and how this can help prevent elbow injuries in softball pitching[22]. Corben et al examined how pitching a lot tires the hip and scapular muscles in addition to those in the shoulder and arm. They also discuss how this fatigue negatively impacts pitch speed and emphasize the importance of strength in preventing it[23]. Oliver et al attempted to describe and identify muscle activation patterns, and discovered the Gluteus maximus was very active during what they describe as phase three (from 3 o'clock to 12 o'clock; transfer of body weight forward; trunk open up to third base; arm reached 180°of elevation) while the Biceps brachii was the most active during what they describe as phase four (from 12 o'clock to 9 o'clock; trunk is open to third base; stride foot plant occurs), and the scapular stabilizers were most active at what they describe as phase two (from 6 o'clock to 3 o'clock; body weight is on ipsilateral leg, trunk is squared toward the batter; arm is elevating to 90)[24]. Maffet et al. used intramuscular electromyography, high-speed cinematography, and motion analysis to analyze muscles involved in a pitch. They discovered many muscle activations, including the supraspinatus muscle firing maximally during arm elevation from the 6 to 3 o'clock position phase, the posterior deltoid and teres minor muscles acting maximally from the 3 to 12 o'clock position phase, and the pectoralis major muscle accelerating the arm from the 12 o'clock position to ball release phase[25]. Similarly, Barrentine et al studied eight softball pitchers to understand the forces on elbow muscles during a pitch but used their findings through the lens of injury prevention[26]. These studies did not prove that strengthening

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these muscles would improve velocity; instead, they focused on injury prevention.

Methods

Participants and Setting

The data in this study were collected from 45 high school-age girls in Massachusetts in the spring of 2025. These athletes gave their consent for filming and the use of their data, and this data was shared with them as part of their training. These athletes were enrolled in the high-level Varsity School program at Planet Fastpitch in Uxbridge, Massachusetts. They were thus self-selecting, generally high school-aged, and had all been working on pitching for many years. The athletes had a mean graduation year of 2027, which corresponded to a high school sophomore at the time, with a standard deviation of 1.5 years, as shown in Table 1 below.

Table 1 Summary Statistics for Graduation Year of Participants

Statistic	Value
Standard deviation	1.4785
Mean	2027.34
Minimum	2025
Maximum	2031
Mode	2029

Procedure

We collected speed, release point, performance metrics, and inhibitors from live pitching for each athlete. Speed (miles per hour), the objective metric, was collected via a radar gun. Each pitcher threw three pitches, and their maximum speed was recorded. Using the fastest pitch, the performance metrics and release point were collected by manually analyzing a video of the pitcher's motion using Onform, a sports video analysis platform, and its embedded stopwatch feature. Onform enabled viewers to analyze videos at 120 frames per second. Lastly, the inhibitors, which are binary true or false, were determined by an expert coach watching the same videos in Onform. One coach watched and evaluated all the videos to minimize bias and variability.

The strength metrics were collected via a series of tests. The pitchers were allowed multiple tries for each test, and their best was recorded. The test results have two decimal places of precision, except for grip strength and vertical jump. The platform used for data collection also included a Power Score, which combines various metrics into a single metric. We treat Power Score as a separate variable. All of the data was entered into Google Sheets.

Table 2 Types of Metrics

Metric Type	Examples
Performance metrics	Lift to land, land to release, stride length
Power metrics	Grip strength, vertical jump, box jump
Inhibitors	Losing space, landing early, drifting

Analytical Approach

To understand the relationships between the various metrics and pitch speed, we performed single and multivariate linear regressions. R^2 was used as our measure of fit, and when computing multiple variable regressions, we used adjusted R^2 because it accounts for multiple variables by adjusting for degrees of freedom, penalizing the addition of extra variables. We also use p-value to determine the significance of each variable in the multivariate regressions ($p<0.05$ or 5%). All regressions presented in this document were computed in Python using the statsmodels.api.ols function running on Google Colab.

In addition to speed, we introduced a new predicted variable, reaction time, based on our understanding of the game of softball. Reaction time is the time the hitter has from when the ball leaves the pitcher's hand to when it reaches the plate. From a hitter's perspective, if we have two pitchers with the same speed, the one who releases the ball closer to the hitter will appear faster because there will be less time to react. Given that we have speed, the location of the pitching rubber (43 feet), and the release point (feet from the rubber), we can calculate reaction time as:

$$ReactionTime = \frac{43 - ReleasePoint}{Speed}$$

With reaction time, we then performed an analysis to speed, using both single and multivariate regressions.

Notably, three of the 45 participants were missing some metrics. The missing values were handled through pairwise exclusion; if an (athlete, metric) pair contained a missing value, both the athlete and the metric were still included in the analysis where possible. As such, some of the metrics used had fewer data points. We account for this in our R^2 and adjusted R^2 values, acknowledging it by including the number of data points used (n) in the tables.

Results

First, the summary metrics of the data were examined using the mean and standard deviation. Then we did the analysis the methodology outlined.

For fastball maximum speed, one standard deviation around the mean is approximately 4.5 mph. For perspective, this is a huge difference - a D1 college softball pitcher throws 60-68

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Table 3 Summary Statistics for All Metrics

Variable	Mean	Standard Deviation
Fastball Maximum Speed	53.682	4.516
Grip Test	81.823	12.985
Broad Jump	6.130	0.565
Power Score	14.540	1.901
Sit Up Throw	12.972	1.916
Seated Chest Pass	14.479	1.491
Land to release	0.127	0.018
Lift to Land	0.474	0.049
Stride length	6.638	0.555

miles per hour, and a D3 college pitcher throws 55-62 miles per hour[27].

The first step of our analysis is a set of single-variable regressions to understand the basic independent relationships between our metrics and speed. First, we consider the performance metrics.

Table 4 Single Variable Regression using Performance Metrics to Predict Speed (mph)

Factor	Coefficient	P value	R^2	Number of Data Points
Land to release (sec)	-130.36	0.0007	0.255	42
Lift to land (sec)	-19.05	0.1921	0.041	43
Stride (feet)	3.14	0.0120	0.144	43

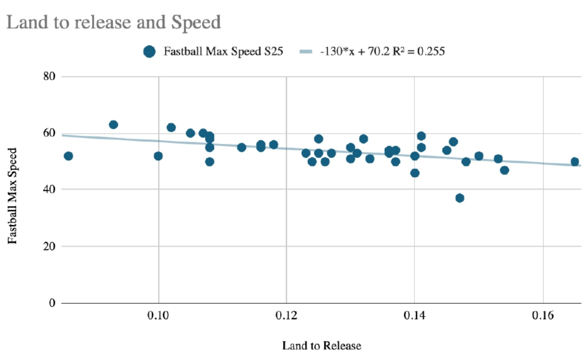

Fig. 1 Relationship between Land to Release and Speed

As shown in Table 4, all three factors impact speed, with land-to-release having the greatest impact, followed by stride and lift-to-land. The table shows that for every 0.1 additional second of land release, the speed reduces by 13 mph; for every 0.1 additional second of lift to land, the speed reduces by 1.9 mph; and for every additional foot in the stride, the speed increases by 3.1 mph. Overall, performance metrics explain some of the variance of speed, but as seen in the relatively low R^2, not by much.

Next, in Table 5, we observe power metrics and speed, and see a slightly stronger relationship.

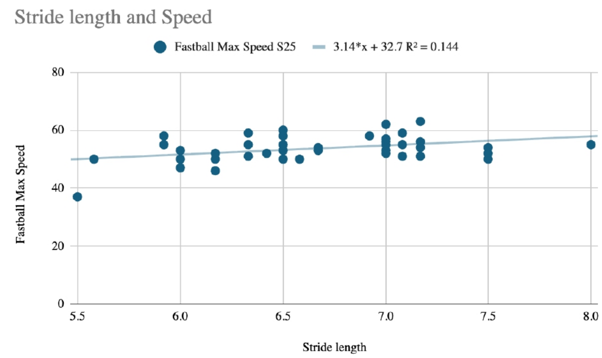

Fig. 2 Relationship between Stride Length and Speed

Table 5 Single Variable Regression between Power and Speed (mph) (Top 5 by R^2)

Variable	R^2	Variable p Value	Number of Data Points
Broad Jump	0.323	0.0001	45
Grip Test	0.314	0.0001	45
Sit Up Throw	0.308	0.0001	44
Seated Chest Pass	0.257	0.0004	44
Power Score	0.253	0.0005	44

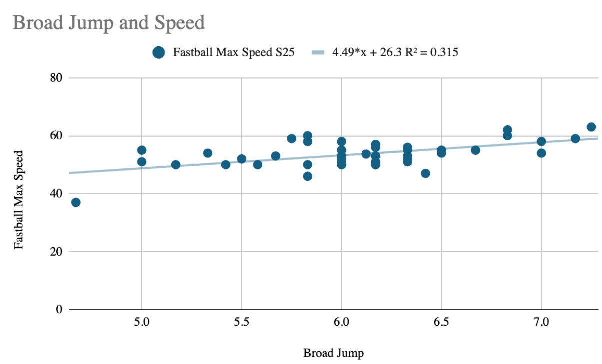

Fig. 3 Relationship between Broad Jump and Speed

The highest R^2 value was 0.32, indicating that power can predict speed to a decent extent. In fact, several power metrics seem to be good predictors. Some include broad jump (0.32), sit-up throws (0.31), grip test (0.31), and seated chest pass (0.26). The R^2 scores are not significantly different, suggesting that overall strength, rather than a particular measure, is important. So far, these are the best predictors of speed.

Next, the inhibitors were examined using a single variable regression. The highest R^2 value was 0.06, indicating that the inhibitors alone do not significantly predict speed.

We turn to two-variable regressions to determine the best two variable model for predicting speed using any combina-

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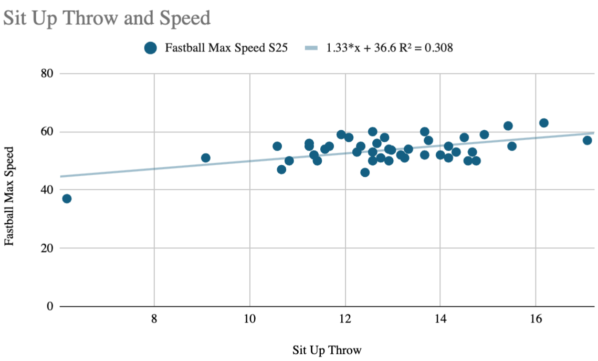

Fig. 4 Relationship between Sit Up Throw and Speed

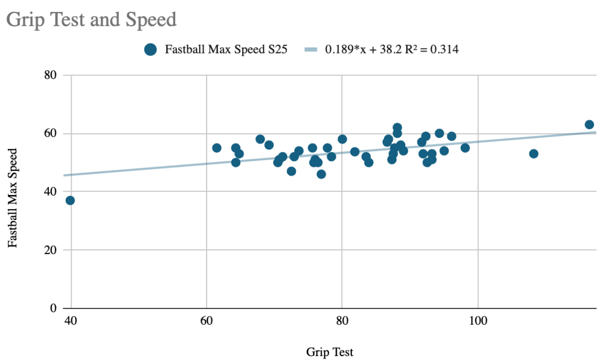

Fig. 5 Relationship between Grip Test and Speed

Table 6 Single Variable Regression between Inhibitors and Speed (mph) (Top 5 by R^2)

Inhibitor	R^2	Number of Data Points
Drifting	0.06	41
Standing up	0.05	42
Pushing	0.05	41
Losing space	0.04	42
Anchoring	0.03	41

tion of power, performance, and inhibitors, in addition to seeing if the metrics are additive.

The adjusted R^2 of the best model is 0.47, the highest so far. Furthermore, the p-values indicate that each predictor, both the strength and performance metrics, has statistically significant predictive power. Additionally, the adjusted R^2 values are relatively close in value, indicating that there is not a significant difference between the selected variables. However, many variables repeat, suggesting that they are important. Every model included at least one power metric. Of the 20 possible variables in this list of 10 two variable models, 15 were power metrics. Only one inhibitor was used (losing space).

Now, the three variable regressions were considered. The best three-variable regressions to predict speed (using any combination of power, performance, and inhibitors) are:

The adjusted R^2 is up to 0.55, which is the best so far. The top four models have p values < 0.05. However, some of the lower-rated models have p-values greater than 0.05 which will be discussed later. It can be observed that grip test appears in every model. Interestingly, 6 out of 10 regressions include an inhibitor, and 8 out of 10 include land to release (performance metric).

As we will elaborate in the Discussion section, this suggests that these variables are additive to one another. For example, inhibitors on their own were not significant, but with power and performance metrics, we improved the adjusted R^2 of 0.55 and a statistically significant p value for the inhibitor variable! Similarly, grip test had the second best R^2 of the power metrics in the single variable regressions. However, it now appears in almost every multivariable regression, suggesting it is important once other factors are controlled for.

Using the same metrics, the analysis was repeated to predict reaction time. Recall that reaction time is the amount of time the hitter has from when the ball leaves the pitcher's hand to reach the plate. The following are tables of single variable regressions between the performance metrics and reaction time:

First, note that stride length is mechanically related to the release point and therefore partially embedded in the reaction-time calculation. However, stride length and release point are not identical ($r = 0.72$), and describe different parts of the motion, so we include it in this table for completeness.

Any associations involving stride length should be interpreted cautiously due to this relationship; therefore, we focus on the other two metrics.

Something interesting to note is that all the coefficients of these performance switched signs (from negative to positive and vice versa) compared to the speed analysis.

Focusing on the other two metrics in Table 9 and referencing Table 4, it can be observed that having a slower land to release can reduce speed (coefficient of -130 and R^2 of 0.255). However, it is positively related to reaction time (positive coefficient of 2.014 and R^2 of 0.253).

We now continue the rest of the analysis for reaction time, starting with the two variable regressions for reaction time.

Like speed, power metrics play a significant role. Of the 20 possible variables, 13 were power metrics again. Also, 16 out of 20 p values were significant.

Finally, the best three-variable regression to predict reaction time (using any combination of power, performance, and inhibitors) was explored.

The highest adjusted R^2 of the chart is 0.552, and 27 out of 30 p values are less than 5%. Like speed, grip test is used in

Table 7 Two Variable Regression using any Metric or Inhibitor to Predict Speed (mph) (Top 10 by Adjusted R^2)

Variable 1	Variable 2	R^2	Adjusted R^2	Variable 1 p Value	Variable 2 p Value	Number of Data Points
Grip Test	Land to release	0.494	0.468	0.0001	0.0005	42
Grip Test	Broad Jump	0.431	0.404	0.0056	0.0055	45
Grip Test	Sit Up Throw	0.431	0.403	0.0049	0.0077	44
Grip Test	Seated Chest Pass	0.418	0.390	0.0017	0.0126	44
Sit Up Throw	Land to release	0.419	0.389	0.0015	0.0130	41
Grip Test	Power Score	0.418	0.389	0.0022	0.0106	44
Grip Test	Vertical Jump	0.417	0.388	0.0004	0.0098	44
Power Score	Land to release	0.418	0.387	0.0023	0.0176	41
Grip Test	Losing space	0.411	0.381	0.00001	0.0390	42
Broad Jump	Land to release	0.403	0.372	0.0035	0.0267	42

Table 8 Three Variable Regression using any Metric or Inhibitor to Predict Speed (mph) (Top 10 by Adjusted R^2)

Variable 1	Variable 2	Variable 3	R^2	Adjusted R^2	Variable 1 p Value	Variable 2 p Value	Variable 3 p Value	Number of Data Points
Grip Test	Land to release	Losing space	0.580	0.545	0.000	0.001	0.027	40
Grip Test	Power Score	Losing space	0.557	0.522	0.001	0.001	0.014	41
Grip Test	Power Score	Land to release	0.551	0.514	0.002	0.049	0.007	41
Grip Test	Land to release	Anchoring	0.551	0.513	0.000	0.001	0.111	40
Grip Test	Sit Up Throw	Land to release	0.541	0.504	0.003	0.078	0.004	41
Grip Test	Seated Chest Pass	Land to release	0.541	0.504	0.001	0.078	0.002	41
Grip Test	Land to release	Marching	0.537	0.498	0.000	0.000	0.231	40
Grip Test	Land to release	Leaning	0.533	0.494	0.000	0.001	0.283	40
Grip Test	Sit Up Throw	Losing space	0.531	0.493	0.001	0.005	0.025	41
Grip Test	Broad Jump	Land to release	0.528	0.491	0.003	0.107	0.008	42

Table 9 Single Variable Regression between Performance Metrics and Reaction Time

Variable	Coefficient	R^2	P Value	Number of Data Points
Stride length	-0.063	0.244	0.001	43
Land to release	2.014	0.253	0.001	42
Lift to Land	0.174	0.014	0.445	43

Table 10 Two Variable Regression using any Metric or Inhibitor to Predict Reaction Time (Top 10 by Adjusted R^2)

Variable 1	Variable 2	R^2	Adjusted R^2	Variable 1 p Value	Variable 2 p Value	Number of Data Points
Grip Test	Land to release	0.50182	0.47627	0.00008	0.00054	42
Grip Test	Power Score	0.48843	0.46347	0.00417	0.00035	44
Power Score	Land to release	0.46881	0.44085	0.00035	0.02229	41
Sit Up Throw	Land to release	0.45983	0.43140	0.00048	0.01229	41
Power Score	Stride length	0.44245	0.41386	0.00060	0.06274	42
Grip Test	Vertical Jump	0.43782	0.41039	0.00045	0.00377	44
Sit Up Throw	Leaning	0.43828	0.40791	0.00001	0.08265	40
Grip Test	Broad Jump	0.43009	0.40295	0.00916	0.00342	45
Power Score	Marching	0.43328	0.40264	0.00001	0.12622	40
Power Score	Leaning	0.43096	0.40020	0.00001	0.13895	40

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Table 11 Three Variable Regression using any Metric or Inhibitor to Predict Reaction Time (Top 10 by Adjusted R^2)

Variable 1	Variable 2	Variable 3	R^2	Adjusted R^2	Variable 1 p Value	Variable 2 p Value	Variable 3 p Value	Number of Data Points
Grip Test	Power Score	Land to release	0.58571	0.55212	0.00259	0.00954	0.00941	41
Grip Test	Land to release	Leaning	0.58041	0.54545	0.00006	0.00030	0.03932	40
Grip Test	Sit Up Throw	Land to release	0.56743	0.53235	0.00440	0.02335	0.00517	41
Grip Test	Power Score	Leaning	0.56807	0.53208	0.00175	0.00060	0.07297	40
Grip Test	Seated Chest Pass	Land to release	0.56247	0.52699	0.00146	0.02971	0.00283	41
Grip Test	Land to release	Losing space	0.56297	0.52655	0.00004	0.00100	0.09423	40
Grip Test	Power Score	Marching	0.56191	0.52540	0.00250	0.00025	0.09962	40
Sit Up Throw	Land to release	Leaning	0.56240	0.52489	0.00016	0.00391	0.03343	39
Grip Test	Vertical Jump	Land to release	0.55774	0.52282	0.00024	0.03457	0.00561	42
Grip Test	Stride length	Losing space	0.55428	0.51814	0.00012	0.00124	0.00627	41

almost all models (9 out of 10). Similar to speed, 6 out of 10 models include an inhibitor.

Discussion

Summary of Key Findings

We were able to create a three variable model that explains over half of the variation in the speed of a softball pitch. Furthermore, it highlights that strength can have significant additive predictive power to performance metrics. The following are noteworthy points discovered in the analysis:

- Overall, we have a simple model with only three variables that explains 58% of the variation in the speed. It is statistically strong with an adjusted R^2 of 0.55, and each variable's p-value was < 0.05.
- The best single variable regression between performance metrics and speed was land to release (R^2 of 0.255). Several power metrics predict speed with a stronger R^2, for example, broad jump (R^2 of 0.32).
- The best two variable regression was grip test and land to release, with an adjusted R^2 of 0.47. This is 21% better than performance alone and 14% better than power alone. Most insightful, we see p-values of <0.0005 for each, meaning that power and performance are additive to each other.
- The inhibitors were not significant on their own, but appeared in the best multivariable models, meaning they statistically enhance the model's fit quality once power is controlled.
- Reaction time, an alternative predicted variable, yields similar conclusions for power metrics but opposite conclusions for performance metrics.

Interpretation and Implications

The results demonstrated that both performance and strength are important in their own right. This is evident in the single variable regressions (Tables 4 and 5). This is consistent with the prior work stated above. Within speed, the most predictive metric is land-to-release, with a meaningful but not particularly strong relationship. This is intriguing because these performance metrics and their mechanics are what pitchers spend time on, yet they are not very impactful on their own.

More importantly, strength and performance metrics are additive to each other. When considering the two variable regressions, the most predictive model utilized grip strength and land to release, which had a higher adjusted R^2 with statistically significant p values, representing a notable improvement over the single-variable models. When combined, they had a 45% stronger relationship than performance alone, significantly improving the model's fit for predicting pitch speed. Moreover, we observed several two-variable models, where combining strength and performance metrics had notably higher adjusted R^2 values compared to the single-variable models, with statistically significant p-values. This demonstrates that neither performance nor strength is a better version of the other, and a pitcher needs both. This adds predictive power to the model and supports the hypothesis that strength is important, which is useful as strength is often overlooked in training programs. While performance metrics are important, for pitchers at Planet Fastpitch who have a solid foundation in performance metrics and mechanics, a key piece for development is to improve their strength. While grip test appears a lot, other power metrics also appear with statistically significant p values, which suggests the predictive benefits are not unique to grip strength but power overall! Together, these findings demonstrate that strength metrics capture important physical qualities that performance metrics alone do not.

We also observe that the inhibitors improve the model's fit quality once power is controlled, even though they were not predictive on their own, as evident in the extremely low R^2 values in the single variable regressions. For example, grip strength and land-to-release, when analyzed individually, had

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an adjusted R^2 of 0.47. However, with the addition of losing space, an inhibitor, the adjusted R^2 increased to 0.55, and losing space had a p-value of 0.027. Additionally, the top ten three variable regressions, sorted by adjusted R^2, each included an inhibitor. Viewed through a softball lens, this is both sensible and constructive. It suggests that the smaller technical elements of a pitcher's form can be important, but only once mechanics and strength are established.

Together, these provide a key contribution of this paper: a predictive model that offers intuitive and practical guidance for practitioners, explaining 58% of the variance in softball pitch speed for this population using only three variables. The model incorporates two domains, kinematic performance metrics and strength-related measures. Each has physical intuition for softball pitchers and has been shown to influence pitch speed. While we consider many metrics, we find that a three variable model performs best. Adding more variables does not increase the adjusted R^2, and in fact, in some of the top three-variable models, the p-values are not statistically significant, suggesting that even two variables are predictive in those cases. This is because grip strength and land to release are good predictors together, capturing the explanatory power of the other variables. This is helpful to coaches and athletes to be able to focus on a small number of things. Finally, considering which variables to use, several interesting points are highlighted in Table 8. First, while there are many significant power metrics, grip test was used in all top ten regressions sorted by adjusted R^2. This suggests that it is important and/or encodes other strength metrics, and both make sense in softball. Grip strength has direct physical relevance to the pitching motion and also serves as a proxy for broader strength, as it tends to improve with many forms of resistance training in which the hands are loaded. Secondly, we observe that multiple grip-strength-based models yield similar results. We identified four models that achieved high explanatory power (adjusted $R^2 > 0.5$) with all predictors statistically significant ($p < 0.05$). The presence of several such models is meaningful, indicating that multiple combinations of variables can capture the core factor of pitch speed, and yet the number is small enough to suggest that the solution space is specific rather than random.

Reaction time, an alternative predicted variable, yields similar conclusions for power metrics but opposite conclusions for performance metrics. Reaction time, as stated before, is the amount of time the hitter has from when the ball leaves the pitcher's hand to reach the plate. If two pitchers have the same speed, the one with the release point closest to the batter will appear faster, and therefore is harder to hit. This can be best seen by comparing Table 4, which considers speed, to Table 9, which considers reaction time. While the R^2 values are relatively similar between the two, it is interesting to note that the coefficients for the performance metrics, notably lift to land and land to release, switched signs. This observation could be meaningful for training, as performance metrics that hinder speed appear to enhance reaction time. If a pitcher has a longer and thus less efficient motion, it does not help speed but may help reduce reaction time by creating a release point closer to the batter. It's also helpful to note that Tables 10 and 11, which repeat Tables 7 and 8, but this time for reaction time, have similar R^2 values, statistically significant p-values, and similar variables selected.

Given our knowledge of the game of softball, these results are applicable. The data indicate that a pitcher's strength is a significant source of speed, as various muscles contribute to power production. For example, lower-body strength is important because the stronger a pitcher pushes off the mound, the more velocity they get. Strong hips allow a pitcher to transfer energy to their arm. Without a strong core, it is harder for a pitcher to stay balanced, which would cause them to lose power. Grip strength enables a firmer wrist snap, resulting in increased speed[1]. However, strength by itself is not enough, and if two pitchers have comparable mechanics, it is reasonable that the stronger pitcher will throw harder.

The results together support the hypothesis that strength is consistently associated with pitch speed for this cohort. Planet Fastpitch can now share these findings with their pitchers so they know targeted and overall areas for strength improvement. While this set of data is limited to pitchers with a strong background and those who have already spent years refining their mechanics, future work could consider the results to generate research ideas for groups with different skill levels and experiences.

Limitations

We acknowledge several potential sources of bias or error in this study. First, we note that many metrics, including the video analysis, involve manual steps, which could introduce errors due to human mistakes and a lack of precision. Further, not only was the sample size small, but the participants were not very diverse. The pitchers were mostly high school students with several years of training experience, so the results may differ for younger girls, male athletes, adults, or those with more or less extensive softball or strength training. We also used only linear models, and perhaps some effects could be captured with non-linear models.

Future Research

The predictive model created provides some hints for a training plan, but it does not capture the entire softball pitch. As a result, this analysis has created several other potential study ideas. A straightforward enhancement would be a larger dataset, which would enable more in-depth analysis, a limita-

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tion of this study. With more participants, factors such as age, height, years of experience, and others could be analyzed statistically, yielding additional insights for athletes and coaches. For example, if a larger dataset were available, handedness could be analyzed; however, this dataset contained only three left-handed individuals. Another idea could be to conduct a longitudinal analysis on the same or a different cohort of athletes to examine the changes in strength in relation to changes in speed and determine if these changes lead to predictive improvements. Additionally, since grip strength may be a proxy for whole-body strength, another study could attempt to tease apart these factors and investigate more deeply which specific areas (such as upper body and lower body) are the most impactful. Another question this work introduces is: assuming there are multiple ways to improve velocity, what is the most efficient way to do so? Some variables may be strongly correlated but difficult to improve, while others might be less correlated but easier to improve. Additionally, at what experience level is strength, to a degree, more important than mechanics? Lastly, this study also raises other questions, such as whether strength plays a similarly significant role in hitting and overhand throwing, and if a similar analysis, combining biomechanical metrics and strength, would be meaningful.

Conclusion

The results together support the hypothesis that strength, a less-studied and often-overlooked attribute, could play a role in the pitching success of athletes who have already spent years refining their mechanics. A simple three-variable model explained more than half of the variation in pitch speed, and every top model included both a performance metric and a strength metric. This demonstrated the additivity of strength, with grip strength appearing repeatedly. We also see that small technical issues, such as inhibitors, only become meaningful once strength and form are already incorporated. Planet Fastpitch can now share these findings with their pitchers so they know targeted and overall areas for strength improvement. This provides pitchers with a roadmap of what they need to work on - mechanics, strength, and refinement. While this set of data is limited to pitchers with a strong background, future work could consider larger and more diverse datasets, as well as deeper analysis, to determine which attributes most efficiently improve velocity.

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