Can We Really Predict Which Football Players Will Succeed?

Jonathan Feldman
Glen Ridge High School, Glen Ridge, New Jersey, USA
jonathan.feldman.2007@gmail.com

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Abstract: Predicting whether a football player will achieve their projected career potential is a key challenge for clubs and scouts. This study analyzes the career outcomes of 8,770 players from the European Soccer Database (2008–2016), using FIFA video game potential ratings as a proxy for projected potential. To account for the increasing difficulty of skill improvements at higher levels, we apply logarithmic scaling when calculating achievement ratios. Predictive models were trained on two cohorts: players with complete career data and those with early-career data (up to age 21). Early-career models achieved moderate predictive performance (ROC AUC = 0.79), reflecting the challenge of identifying long-term success based on limited early observations. SHAP analysis shows that growth trajectory features, including early improvement and development patterns, contribute more to success predictions than static physical or technical attributes. We define success as fulfilling projected potential according to the FIFA rating system – a standardized but subjective benchmark. While this does not capture all real-world outcomes, it enables large-scale analysis of developmental trajectories. These results suggest that tracking player development over time provides better guidance for talent decisions than relying solely on early physical assessments.

1 INTRODUCTION

Predicting a football player's long-term career success is a key challenge for scouts, coaches, and analysts. Early assessments of potential influence recruitment decisions, training investments, and transfer valuations. Despite growing access to player data, many highly rated young players do not reach their projected potential. In our dataset, only **48.6%** of players with full career trajectories achieved at least 95% of their projected potential, highlighting the difficulty of early talent forecasting.

Explaining why some players fulfill expectations while others underachieve remains an open problem in sports analytics. Most existing research focuses on short-term performance metrics or static evaluations, often ignoring the combination of demographic, physical, technical, and psychological factors that shape career outcomes.

This study analyzes these factors using the European Soccer Database (Mathien, 2016), which contains detailed player and match data from major European leagues between 2008 and 2016. Player potential scores in this dataset are drawn from FIFA video game ratings, providing a consistent, though subjective, proxy for projected potential and enabling longitudinal analysis of player development.

We examine which player attributes are most associated with fulfilling or failing to meet projected potential. Using correlation analysis and predictive modeling, we assess how factors such as age, position, technical skills, and mental attributes relate to long-term career outcomes. This analysis contributes to a better understanding of player development patterns and supports efforts to improve data-driven approaches in scouting and talent management.

Throughout this study, we use the term *football*, also known as *soccer* in some regions, to refer to the sport governed by FIFA.

2 RELATED WORK

Talent identification and player development have long been key challenges in sports science and analytics. Traditional scouting practices typically emphasize early physical maturity and observable technical skills, but these approaches often fail to predict long-term success accurately. (Meylan et al., 2010) and (Sarmento et al., 2018) highlight the importance of considering physiological, psychological, and tactical characteristics in player evaluations, while (Güllich, 2014) show that early specialization may lead to unrealistic expectations and suboptimal developmental outcomes.

Broader reviews by (Vaeyens et al., 2008) and (Reeves et al., 2018) stress that effective talent identification should incorporate sociological factors and developmental variability rather than relying solely on early performance metrics. (Dugdale et al., 2020) provide longitudinal evidence that success at the academy level does not guarantee professional achievement, underscoring the need for models that account for developmental trajectories.

With the increasing availability of player data, machine learning methods have become popular in football analytics. Schumaker et al. (Schumaker et al., 2010) explored early applications of predictive modeling for sports outcomes, while more recent studies by (Decroos et al., 2019) and (Power et al., 2017) introduced sophisticated frameworks for valuing individual player actions and decision-making using match event and tracking data. (Pappalardo et al., 2019) also contributed a standardized dataset to support reproducible spatio-temporal analysis in football.

In parallel, research has increasingly emphasized model interpretability in sports prediction. (Ribeiro et al., 2016) and (Lundberg and Lee, 2017) established foundational approaches to model explainability, which have since been applied in football settings to increase transparency in player evaluation. (Molnar, 2022) offers a comprehensive guide to interpretable machine learning, while (**?**) proposed a fuzzy logic framework for holistic player evaluation.

(Gudmundsson and Horton, 2017) provided a broad survey of spatio-temporal analysis techniques in team sports, highlighting the importance of contextual player behavior. Meanwhile, (van Arem et al., 2025) applied explainable machine learning models to forecast both player development and market value, demonstrating how predictive techniques can support strategic decision-making. Similarly, (Baouan et al., 2022) investigated which performance indicators are most predictive of future player value, reinforcing the relevance of longitudinal data in assessing career potential.

The role of AI in scouting and player development is also gaining traction in media and industry reports (Vicente, 2024; Guardian, 2025), suggesting a broader shift toward data-driven decision-making in football organizations.

Despite these advances, few studies have directly investigated whether players fulfill externally assigned career potential ratings, such as those provided by the FIFA video game series. These ratings, although subjective, are widely used in football analytics due to their consistency across seasons and player cohorts (Mathien, 2016). Building on this line of research, our study analyzes over- and underachievement patterns using these potential scores and examines which early-career features most effectively predict long-term outcomes.

2.1 Datasets

2.1.1 Data Source

We use the publicly available FIFA Player Dataset compiled by Hugo Mathien (Mathien, 2016), which contains player data from EA Sports' FIFA video game series for the years 2008 to 2016. The dataset includes player demographics, physical attributes, and skill evaluations across multiple seasons. The *overall rating* and *potential* scores are based on subjective assessments from the game's expert panels, representing perceived current ability and projected career potential.

The dataset covers approximately 11,000 players and over 300,000 player-season records, providing a large sample for analyzing player development patterns. These ratings reflect subjective perceptions and should be treated as estimates of expected career success rather than objective performance measures.

We primarily use two tables from this dataset:

- *Player:* Contains static information such as birth date, height, and weight.
- *Player_Attributes:* Contains time-stamped records of player ratings and skill attributes, including overall rating, projected potential, and technical and physical skill scores.

While the FIFA video game series is primarily a commercial entertainment product, its player ratings are informed by extensive scouting networks, expert panels, and real-world performance observations. These ratings have become a de facto standardized resource in football analytics due to their broad coverage, longitudinal consistency, and accessibility (Baouan et al., 2022; Mathien, 2016). Although subjective, they provide a uniform proxy for projected player potential across multiple seasons and cohorts – attributes that are rarely available in open-access datasets. As such, they are widely used in both academic studies and industry analyses to explore patterns of player development and market valuation.

2.1.2 Preprocessing

To ensure sufficient coverage for modeling career trajectories, we retained players with at least eight recorded ratings. Player age was calculated dynamically at each observation, and data was limited to ages 16 to 40 to focus on active professional careers. The final dataset included 8,770 players. Of these, 2,212 had complete longitudinal records suitable for modeling final career outcomes, and 4,683 had at least three recorded ratings before age 21, supporting early-career prediction experiments. These groups are not mutually exclusive; some players appear in both cohorts.

Final predictive analyses were conducted using players with complete data for all engineered features and target variables to ensure consistency and reliability. For binary classification, players were labeled as achievers if their final achievement exceeded 95% of their projected potential; those below this threshold were classified as underachievers. This cutoff strikes a balance between a strict definition of success and maintaining a sufficient number of positive cases for modeling.

While this achievement ratio offers a quantifiable proxy for career fulfillment, it remains a subjective and indirect measure. Specifically, it does not necessarily reflect real-world career accomplishments such as international caps, top-league appearances, or major tournament victories. Therefore, although useful for statistical modeling, this metric should not be interpreted as a definitive indicator of career prestige or professional impact.

2.2 Feature Extraction

We derived over 40 features capturing player development and skill progression.

Adjusted Achievement Ratio Over Time. To capture player development over time, we computed an *adjusted achievement ratio* at each observation rather than relying only on final ratings. This metric tracks how players progress toward their projected potential throughout their careers.

The adjusted achievement ratio at time t is defined as:

$$\text{Adj. Achv. Ratio}_t = \frac{\log(1+\text{Rating}_t - \text{B})}{\log(1+\text{Potential}_t - \text{B})}$$

where:

- Rating_t is the player's overall rating at time t,
- Potential_t is the player's projected potential at time t,
- B is a baseline value set to 30, representing the minimum professional-level rating.

We excluded cases where $\text{Potential}_t \leq \text{B}$ to avoid invalid values in the logarithm. The logarithmic scaling accounts for diminishing returns, where improving from a rating of 40 to 50 is easier than improving from 80 to 90.

For each player, we summarized this ratio using the following aggregate features:

- Mean adjusted achievement ratio across all time points.
- Maximum adjusted achievement ratio reached during the career.
- Final adjusted achievement ratio at the last recorded rating.
- Achievement growth trend, calculated as the slope of a linear regression over the adjusted ratios.

Additional Feature Groups

- Growth Metrics: Early growth (up to age 21), late growth (post-21), total growth, growth rate, maximum one-year improvement, and growth volatility.
- Achievement Ratios: Both linear and logarithmic versions measuring how closely a player approached their projected potential.
- Skill Aggregates: Mean, maximum, and final recorded values for stamina, sprint speed, dribbling, finishing, and strength.
- Physical and Categorical Attributes: Height, weight, preferred foot, and work rate preferences.

Categorical attributes were encoded using label encoding, and numerical features were standardized using Z-score normalization to ensure comparability across features.

Table 1 lists the final set of features used in model training. These were selected from the latest available player attributes after removing highly correlated or leaky variables. Categorical features were label-encoded and all numeric values were standardized using Z-score normalization.

2.2.1 Feature Correlation Analysis

The correlation heatmap in Figure 1 shows several patterns in the relationships between features:

- Strong Positive Correlations: The *early achievement ratio* and *final achievement ratio* show strong positive correlations with career progression metrics such as *growth rate*, *final rating*, and *strength_final*. This supports their relevance for modeling career outcomes.

Table 1: Final Features Used in Modeling

Feature	Type / Description
Age	Numeric (latest observation)
Preferred Foot	Categorical (left/right)
Att. Work Rate	Categorical (high/med/low)
Def. Work Rate	Categorical (high/med/low)
Vision	Numeric (passing awareness)
Aggression	Numeric (duel intensity)
Positioning	Numeric (attack positioning)
Acceleration	Numeric (speed buildup)
Sprint Speed	Numeric (top speed)
Stamina	Numeric (fatigue resistance)
Strength	Numeric (physicality)
Dribbling	Numeric (ball control)
Finishing	Numeric (shot accuracy)
Short Passing	Numeric (pass accuracy)

- Athleticism Attributes Show Weak Correlations with Long-Term Success: Attributes related to speed and acceleration (e.g., *sprint_speed*, *acceleration*) have weak or even negative correlations with achievement ratios and career milestones. This suggests that early athleticism alone may not strongly predict long-term success, possibly because these physical traits peak early and do not directly reflect technical or tactical development.
- Technical and Tactical Skills Show Stronger Associations: Features such as *vision_mean*, *short_passing_mean*, and *positioning_mean* show moderate to strong positive correlations with achievement metrics. These skills appear to contribute more consistently to long-term player development.
- High Overlap Between Aggregated Features: Many features were recorded as mean, max, and final values for the same skill (e.g., stamina, strength, dribbling), leading to strong correlations often exceeding 0.95. To reduce redundancy and avoid instability in modeling, we excluded these overlapping variants and retained a simplified feature set. Only non-redundant, numeric features were used in our classification experiments after dropping potential sources of leakage.
- Growth Patterns and Final Achievement: *Max_1yr_growth* and *growth_volatility* show moderate positive correlations with final ratings and achievement ratios. This suggests that players with late physical development or more variable growth trajectories can still achieve high career outcomes, potentially reflecting late specialization or delayed maturity.
- Negative Correlations with Total Growth: *Total_growth* shows negative correlations with several performance-related features. This may indicate that players requiring large improvements to reach their final ratings started from lower initial ratings, complicating interpretations of their development trajectories.

2.2.2 Descriptive Analysis of Key Features

Table 2 summarizes key features related to player development and career outcomes. On average, players gain 13.9 rating points over their careers, with most of that improvement occurring before age 21. Final ratings show substantial variability, reflecting diverse career trajectories.

These patterns suggest that early development may play a central role in determining long-term outcomes and motivate further modeling of how physical, technical, and cognitive attributes influence career progression.

Table 2: Descriptive Statistics of Key Features

Feature	Mean	Std Dev	Min	Max
Early Growth	8.24	5.10	-3.0	20.0
Late Growth	5.67	4.85	-2.0	18.0
Growth Rate	1.20	0.65	0.0	3.5
Stamina Mean	65.8	10.5	40.0	90.0
Strength Max	70.3	15.2	30.0	95.0
Final Rating	72.5	5.40	50.0	93.0

Figure 2 shows the distributions of selected player attributes used in modeling:

- Physical Attributes: Acceleration (Figure 2a) is right-skewed, with most players falling between 70 and 80. Extremely high acceleration is rare, and its marginal benefit may diminish beyond a certain level. Height (Figure 2b) is approximately normally distributed around 180–185 cm. While not strongly correlated with career outcomes, height influences positional roles: taller players often appear in defensive or goalkeeping positions, while shorter players are more common in attacking and midfield roles.
- Growth Patterns: Figures 2c and 2d show that early growth tends to be modest, with only a small subset of players improving rapidly before age 21. Late growth is more limited overall, suggesting that early development has a stronger influence on final ratings.
- Achievement Ratios: The final achievement ratio (Figure 2e) is concentrated near 1.0 for many players, but a substantial number fall short of their projected potential, motivating further analysis of underachievement.

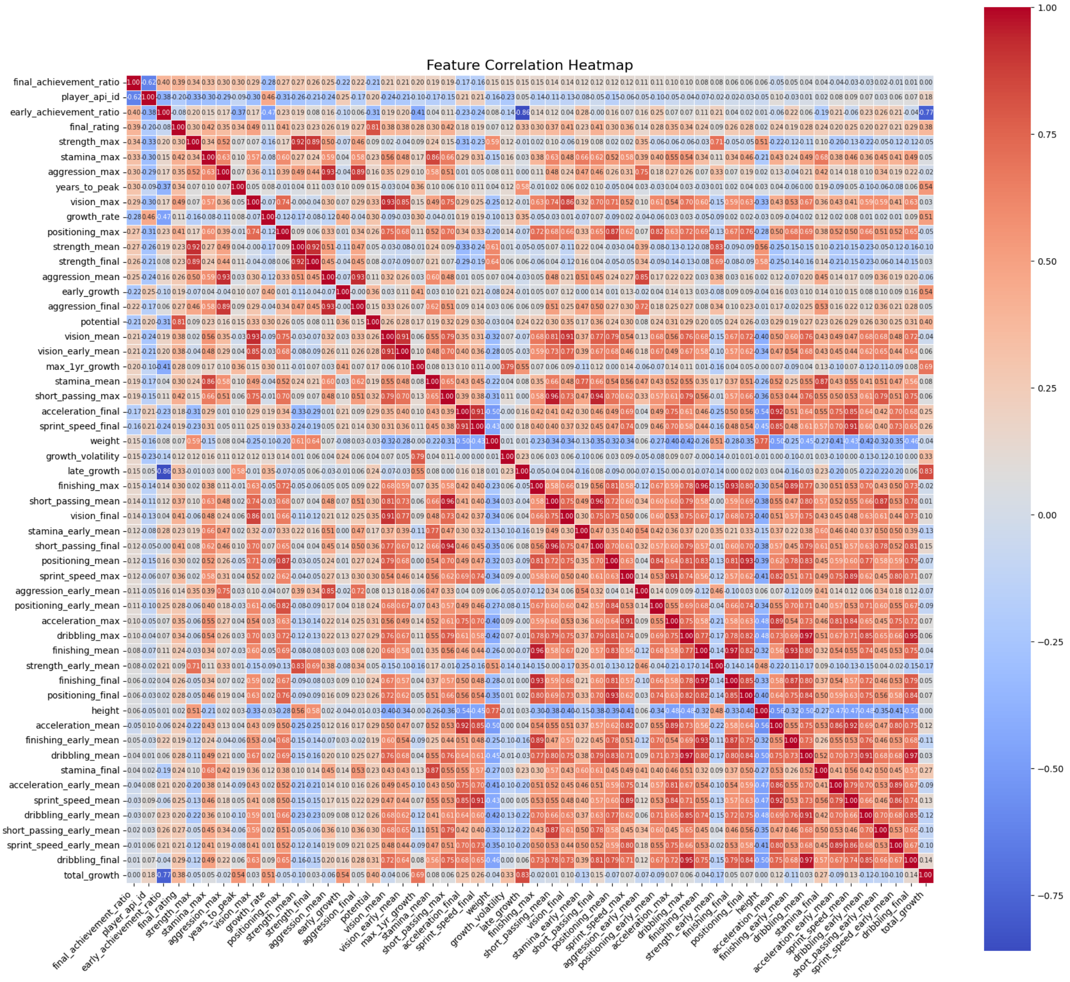


Figure 1: Correlation heatmap of extracted features. Strong positive correlations appear in red, and negative correlations in blue.

- Age and Career Coverage: Figure 2f shows that most player records occur between ages 24 and 26, consistent with typical peak performance years. This supports the dataset's suitability for analyzing full career trajectories.
- Achievement Class Distribution: As shown in Figure 2g, the dataset includes a modest class imbalance, with underachievers slightly outnumbering achievers. This was accounted for in modeling through class balancing strategies.

This descriptive analysis supports the importance of early career development and suggests that while physical traits may influence role-specific performance, technical and cognitive attributes likely contribute more to long-term success. These observations informed both the selection of input features and the modeling strategies used in the next sections.

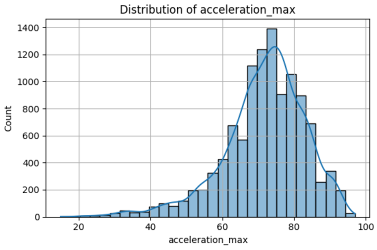
3 MODELING AND ANALYSIS

We used the subset of 2,212 players with complete career trajectories to train and evaluate models predicting final achievement outcomes. This included both regression and classification tasks using the full set of engineered features.

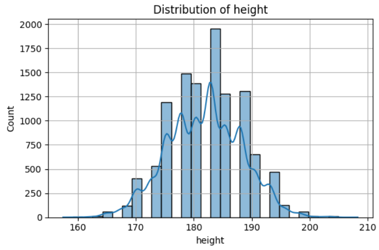
3.1 Regression Modeling

The regression models predicting final achievement ratio were trained on the 2,212 players with complete longitudinal records, ensuring that all growth-related features and final outcomes were fully observed.

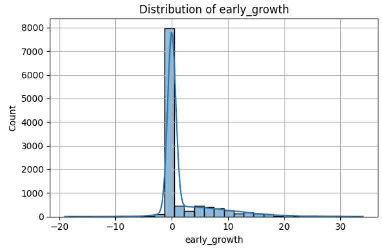
We trained an XGBoost regression model to predict the final achievement ratio using the engineered features. After controlling for potential information leakage by removing features directly related to final outcomes (such as final rating, potential, and



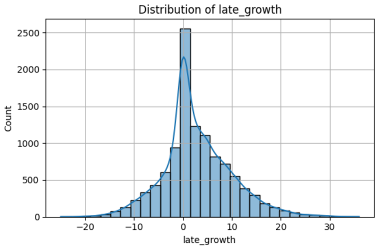
(a) Acceleration Distribution



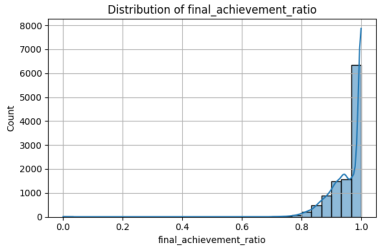
(b) Height Distribution



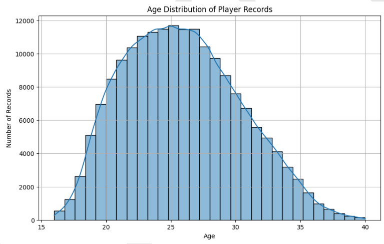
(c) Early Growth Distribution



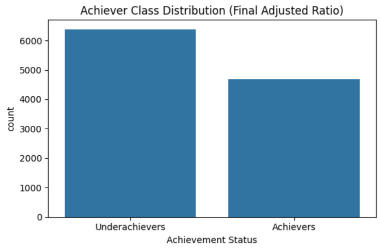
(d) Late Growth Distribution



(e) Final Achievement Ratio



(f) Age Distribution



(g) Achievement Class Distribution

Figure 2: Distributions of selected features relevant to player development, physical attributes, and achievement outcomes.

early achievement ratio), the model achieved an R^2 of 0.48. This reflects the inherent difficulty of forecasting long-term success based on early-career data.

3.2 Feature Importance and Interpretation

We applied two approaches to interpret the model's predictions:

- XGBoost's gain-based feature importance, which estimates each feature's contribution to reducing prediction error.
- SHAP (SHapley Additive exPlanations) (Lundberg and Lee, 2017), which quantifies the marginal impact of each feature on model output across samples.

SHAP Analysis. Figure 3 presents the SHAP results for the leakage-controlled model.

- Growth-related features such as *growth_rate*, *total_growth*, and *years_to_peak* contributed most to prediction accuracy. These indicators of developmental trajectory were more informative than static skill ratings.
- Physical and technical skills had a moderate influence. Attributes such as *stamina* and *strength* ranked lower but still contributed meaningfully. Technical features like *vision* and *positioning* had limited predictive value when trajectory-based features were included.

Although some technical and physical skills correlate with career outcomes when considered individually, their predictive value diminishes once growth-related features are included. This suggests that player development trajectories capture much of the variance associated with career outcomes.

The final R^2 result highlights the challenge of forecasting long-term success from limited early-career data. Future work should validate these findings on external datasets to assess their generalizability.

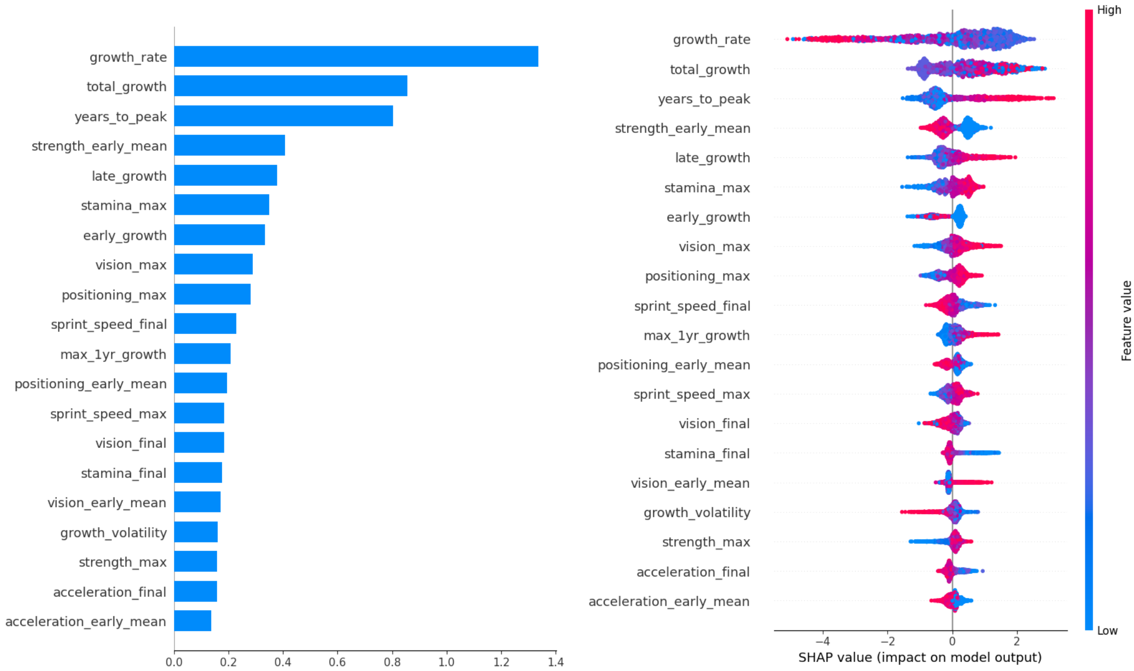


Figure 3: SHAP analysis results: (Left) Mean absolute SHAP values; (Right) SHAP summary plot showing feature impact and direction.

Interpretation of Regression vs Classification Performance. Although both regression and classification models were trained on overlapping feature sets, their performance metrics are not directly comparable due to the difference in task framing and evaluation criteria. The regression model aims to predict a continuous achievement ratio, which is a more granular and challenging target, and achieved an R^2 of 0.48. In contrast, the classification model simplifies the problem to a binary outcome (achiever vs. underachiever), which is easier to separate, especially when using engineered features like growth trends. Furthermore, the classification model benefits from thresholding near the extremes (e.g., 0.95 cutoff), which can lead to higher ROC AUC scores even if underlying predictions are not highly precise. To quantify variability, we conducted 5-fold cross-validation and observed a mean ROC AUC of 0.79 (± 0.02), indicating consistent discriminative performance across folds. This partial decoupling between the continuous and binary framing explains why the classifier shows higher discriminative power (ROC AUC $\approx$ 0.79) despite relying on similar inputs. This also reinforces the importance of choosing modeling objectives that align with practical decision-making goals in scouting and development contexts.

3.3 Predictive Modeling and Evaluation

In addition to regression modeling, we trained a Random Forest (Breiman, 2001) classifier to predict whether a player would exceed 95% of their projected potential.

Model performance was evaluated using 5-fold cross-validation to ensure robustness and mitigate the effects of random splits. All results reported reflect average performance across the validation folds.

Early-Career Prediction Results. Using only data available before age 21 and excluding features that directly encode career outcomes, the model achieved moderate predictive performance: Accuracy of 73.95% $\pm$ 1.42%, F1 Score of 0.6250 $\pm$ 2.14%, and ROC AUC of 0.7925 $\pm$ 1.62%.

These results highlight the difficulty of predicting long-term career success based solely on early-career data. While the model can differentiate between likely achievers and underachievers better than chance, predictive accuracy remains limited, reflecting the complexity of player development.

Class-Wise Performance. The model demonstrates higher precision than recall, indicating greater confidence in identifying players who meet their projected potential but frequent difficulty detecting underachievers. This suggests that the model tends to overestimate success based on early-career data.

- Precision: 73.08% ± 4.97%
- Recall: 54.73% ± 1.65%

This imbalance highlights the model's tendency to favor positive predictions (achievers), while missing many players who eventually underachieve. Identifying late bloomers and players who fail to reach their projected potential remains a key challenge.

Error Analysis. False positives typically involve players who show early promise but fail to improve, while false negatives are often late bloomers who develop after a slow start.

SHAP analysis confirms that growth trajectory features like *growth_rate*, *total_growth*, and *years_to_peak* are more predictive of success than static early-career attributes. However, identifying late bloomers remains difficult.

Despite moderate ranking ability, the model struggles to predict underachievement accurately, underscoring the need for longitudinal development tracking and caution in early talent assessments.

3.4 Error Analysis: The Limits of Early Predictions and the Myth of Early Promise

Despite achieving moderate quantitative performance, our predictive model exhibits systematic errors that reveal important limitations in using early-career metrics to forecast long-term success. Specifically, the model tends to *overestimate* players who demonstrate strong early physical attributes and high initial ratings, while failing to recognize *late bloomers* who develop their potential after a slower start.

False Positives: The Pitfall of Early Promise. Table 3 summarizes players who were predicted to achieve their projected potential but ultimately underachieved.

Table 3: False Positives: Predicted Success but Underachieved

Player Name	Final Achv.	Early Rating	Stamina	Growth Rate
Anssi Jaakkola	0.93	49.00	43.5	1.50
Lucas	0.94	64.60	58.6	-1.17
David Barron	0.89	53.25	54.0	3.25
Ismael Aissati	0.95	72.00	76.2	0.20
Michele Rinaldi	0.88	66.00	72.0	1.00

The columns in Table 3 and Table 4 provide the following information:

- **Final Achv.**: The player's *final achievement ratio*, calculated as actual career performance relative to projected potential. Values below 1.00 indicate underachievement.
- **Early Rating**: The average player rating before age 21, calculated as a simple mean of all available ratings during this period. This value reflects the player's observable abilities before reaching maturity and is used directly as a predictive feature without transformation.
- **Stamina**: Average stamina rating during early career (before 21), indicating physical endurance.
- **Growth Rate**: The average year-over-year change in player rating before age 21. This is calculated as:

$$\text{Growth Rate} = \frac{1}{N}\sum_{i=1}^{N}\left(\text{Rating}_{i+1} - \text{Rating}_{i}\right) \quad (1)$$

where N is the number of consecutive rating observations before age 21. Negative or near-zero values indicate stagnation or decline in early-career performance.

Despite strong early ratings and stamina, these players underachieved due to limited or negative growth, demonstrating the model's tendency to overestimate future success based on early promise without accounting for sustained development.

False Negatives: Overlooking Late Bloomers. We define *late bloomers* as players who show limited or negative growth before age 21 but experience significant improvement in their early to mid-twenties. Table 4 shows players who were predicted to underachieve but ultimately fulfilled or exceeded their projected potential.

Table 4: False Negatives: Predicted Failure but Succeeded

Player Name	Final Achv.	Early Rating	Stamina	Growth Rate
Konstantin Engel	1.00	48.33	48.67	0.00
Krisztian Nemeth	0.99	69.00	63.40	0.00
Kanu	1.00	64.50	60.00	0.00
Jakub Rzezniczak	1.00	61.67	77.00	0.00
Maciej Korzym	1.00	58.75	62.00	-0.40

While these players fulfilled their projected potential according to the dataset metrics, only a subset achieved international recognition. Notably, Nwankwo Kanu became a globally celebrated player

with major titles at both club and national levels. Others, such as Krisztián Németh and Jakub Rzeźniczak, enjoyed successful domestic careers or moderate international appearances but did not reach global stardom. This distinction makes clear that meeting projected potential does not always translate to elite-level success and highlights the complexity of defining and evaluating ”success” in football careers.
These cases illustrate the challenge of predicting success for late bloomers. Despite modest early-career profiles and limited growth, some players achieved remarkable careers, emphasizing the importance of factors beyond early observable performance.

Fulfilling projected potential (Final Achv. ≈ 1.00) reflects meeting expectations based on statistical projections, but does not necessarily equate to achieving stardom or international fame. For example, while Konstantin Engel fully met his projected potential, his career remained largely within lower-tier German leagues. In contrast, Nwankwo Kanu, also classified as a false negative, became an internationally celebrated player despite modest early metrics.

These cases demonstrate that achieving statistical success according to projected metrics does not always align with real-world career prestige. This reinforces the importance of incorporating broader qualitative factors, such as psychological resilience, career opportunities, and non-linear development paths, when evaluating talent.

Correct Predictions: When the Model Gets It Right. Beyond its misclassifications, the model also successfully identified players who either fulfilled or failed to meet their projected potential. These examples demonstrate that early-career metrics can be informative predictors when career trajectories follow more expected development patterns.

Table 5: True Positives: Correctly Predicted Success

Player Name	Final Achv.	Early Rating	Growth Rate
Ruben Perez	0.99	65.20	2.40
Marco Perez	0.96	70.00	-3.00
Antoine Rey	1.00	41.00	0.00
Michal Svec	0.96	61.00	-0.25
Antonio Candreva	1.00	60.33	1.33

In Table 5, we highlight players who achieved their projected potential and were correctly classified by the model. Notably, Ruben Perez and Antonio Candreva showed strong early ratings and positive or stable growth. Despite some irregularities, such as negative growth in Marco Perez, the model correctly identified these players as likely achievers.
Table 6 shows examples of correctly predicted underachievers. These players exhibited moderate early ratings and minimal or no growth, aligning with the model’s underachievement prediction. This supports the model’s effectiveness in identifying stagnating players early in their careers.

Table 6: True Negatives: Correctly Predicted Underachievement

Player Name	Final Achv.	Early Rating	Growth Rate
Mikhail Sivakov	0.85	56.00	0.00
Rafael Dias	0.94	58.75	0.00
Garry Wood	0.85	55.00	0.00
Jamie Mole	0.83	60.50	0.50
Amaury Bischoff	0.88	66.00	0.00

Implications for Talent Identification. These findings support prior work in sports science that cautions against an overreliance on early specialization and static performance metrics (Sarmento et al., 2018; Vaeyens et al., 2008). While early career assessments offer valuable insights, they often fail to capture the complex developmental trajectories of athletes. In particular, identifying late bloomers remains a significant challenge for data-driven models.

Future work should explore incorporating additional factors such as injury history, psychological assessments, and changes in coaching environments to improve predictive accuracy. Ultimately, while machine learning models can assist in talent evaluation, they should complement rather than replace expert judgment and longitudinal scouting efforts.

3.5 Comparing Predictive Value Across Career Phases

To better understand how the timing of observed data affects long-term prediction, we compared three experimental setups: (1) early-career only (ages ≤ 21), (2) developmental-phase only (ages 22–26), and (3) a combined pre-peak window (ages ≤ 26). Each model used the same feature types and binary target (achiever vs. underachiever based on final achievement ratio ≥ 0.95).

Performance Summary. As shown in Table 7, the model trained solely on developmental-phase data achieved the highest F1 score (0.86), outperforming both early-career (0.63) and full pre-peak (0.77) models. However, the early-career model achieved the highest ROC AUC, indicating slightly better class separation despite lower overall accuracy. These results suggest that mid-career development offers stronger predictive signals for identifying achievers, but early patterns still carry useful discriminative information.

Interpretation. The full pre-peak model benefits from access to both early promise and mid-career trajectory, yielding a balanced compromise between precision and recall. In contrast, the developmental-phase-only model excels at identifying likely achievers, but with more false positives, possibly due to survivor bias: players still active at 22–26 are more likely to succeed. The early-career model, while less accurate overall, may better capture cases of under-achievement and developmental stagnation.

Table 7: Comparison of Prediction Performance Across Career Phases

Experiment	Age Range	F1 Score	ROC AUC
Early-Career	≤ 21	0.6250	**0.7925**
Full Pre-Peak	≤ 26	0.7746	0.7905
Developmental Only	22–26	**0.8596**	0.7374

These results highlight the importance of longitudinal observation: while early ratings offer some signal, the clearest indicators of long-term success emerge during the professionalization phase. Combining early and mid-career signals yields strong results overall, but continued development remains the most decisive factor.

4 Discussion

This study examined whether football player career outcomes can be predicted using performance trajectories extracted from longitudinal in-game data. We found that growth metrics observed between ages 22 and 26 were more predictive of long-term potential fulfillment than early-career signals alone. While combining early and mid-career data improved classification performance, developmental-phase indicators consistently offered the strongest signal for identifying likely achievers.

These findings support the idea that early static assessments, such as initial ratings or physical attributes, are insufficient for forecasting long-term outcomes. In contrast, developmental patterns such as growth rate, volatility, and late improvements provide more robust predictive value. This highlights the importance of tracking player progression rather than relying on early promise. It also implies that scouting systems emphasizing sustained progress during early adulthood, rather than early peak performance, may better identify overlooked potential.

It is important to clarify that in this study, "success" is operationalized as achieving at least 95% of a player's projected potential rating, as assigned in the FIFA dataset. While this offers a consistent, quantifiable proxy for perceived promise, it does not necessarily reflect professional prestige, international accolades, or financial achievement. Rather, it captures alignment with expectations as encoded in a widely used evaluative framework.

Our analysis also revealed systematic model biases. Players with strong early physical metrics but little follow-through were often overestimated, while late bloomers with slow starts were frequently missed. This reflects the inherent limitations of early-career prediction, even with engineered growth features.

5 Limitations and Future Work

A key limitation of this study is its reliance on the FIFA dataset (2008–2016), where projected potential ratings are based on expert assessments from a commercial video game. These ratings reflect perceived promise, not confirmed professional success, and may be influenced by media exposure, reputation, or other non-performance factors. As a result, our models predict alignment with subjective expectations in the FIFA system, not real-world outcomes such as top-tier appearances, transfer fees, or international recognition.

This distinction matters for generalizability. A player may meet their FIFA potential but still fall short of elite professional standards, or may exceed expectations that were never reflected in their early ratings. While our results shed light on the predictability of perceived potential, they do not directly apply to scouting systems based on different goals or data.

Another limitation is that our models exclude many contextual factors that can strongly affect a player's career. These include injury history, mental resilience, coaching environment, and socio-economic background. Without such data, the models may miss key drivers of unusual or nonlinear development paths. In addition, the findings have not yet been tested on newer player cohorts, so their relevance over time remains uncertain.

Despite these limitations, the FIFA dataset remains useful for large-scale longitudinal analysis. It provides structured, consistent player records across development stages – something that many real-world datasets, especially proprietary or region-specific ones, still lack.

Future work should extend this analysis to alternative datasets that track objective performance metrics, such as club logs, market valuations, or match-level statistics. Incorporating richer contextual signals and validating on more recent player cohorts will help assess whether the same developmental predictors hold across different settings and time periods.

6 Conclusion

Our findings suggest that models incorporating longitudinal development features can moderately predict whether players will fulfill their projected potential. Growth trajectories, not early static assessments, are the strongest predictors of future alignment with expectations.

While standardized ratings such as those used in FIFA data provide a scalable basis for analysis, they offer only a partial view of real-world success. Predictive modeling should be used to complement, not replace, expert judgment, especially when evaluating players who may follow nonlinear or delayed development paths.

Ultimately, this work contributes to a growing body of research suggesting that the key to understanding future potential lies not in early ratings, but in how players improve, adapt, and grow across their developmental years.

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Code and Data Availability

All code and analysis notebooks used in this study are available at: `https://github.com/jonfeld/icsports2025`.

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