

The Factors in Professional Soccer Can Lead to Players Injuries

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Abstract. From an operational perspective, player injuries impair professional sports teams through match absences, tactical discontinuity, and long-term career attrition. While the absence of a pivotal athlete significantly affects results, even non-key player injuries degrade squad stability and depth. Consequently, analyzing injury risk factors is imperative for enhancing team outcomes, necessitating an objective metric for injury severity. Monetizing absence-related loss offers a quantifiable and management-aligned measure well-suited to this task.

Keywords: Football analytics, Correlation coefficient, risk of injuries, Physical confrontation, match-loss

1. Introduction

Football, known as soccer in some regions, has an unparalleled influence worldwide, transcending cultural and geographical boundaries. It is more than just a sport; it is a powerful social phenomenon that unites people across diverse backgrounds. Major events like the FIFA World Cup capture the attention of billions, fostering a sense of global community and shared excitement.

According to data, all clubs in the top 10 of player market values are powerhouses. Although the Premier League does not have any teams in the top three, it boasts five clubs in the top 10—Manchester City, Manchester United, Chelsea, Arsenal, and Liverpool—representing a significant advantage for the Premier League among elite clubs. Additionally, in the rankings of the top 20 and top 50 clubs, the Premier League has seven and 15 clubs listed, respectively, leading among the top five leagues. This demonstrates that the Premier League is not solely reliant on a few big teams.

The detrimental effects of injuries on football players—ranging from derailed development and chronic physical impairment to mental health challenges—fundamentally threaten athletic careers. Our data further reveal a slightly higher incidence of injury among senior players within the studied group. This finding is consistent with the risk factors previously identified by Arnason et al.

In our research, we will focus on the physical condition of football players, average yellow card occurrences per match, total yellow cards, ground confrontation, and header confrontation to study the relationship between these factors and the risk of injury for players. In conclusion, we found that the physical condition of football players has little correlation with the risk of injury, while factors that reflect the players' on-field behavior show a certain degree of relevance to injury risk.

2. Data and tools

In this section, we briefly describe the data sets we used and tools in our football analysis.

2.1. Data selection

In the beginning, we tend to collect a whole team's injury record for two or three seasons (<https://www.tzuqiu.cc/stats.do>, <https://m.7m.com.cn/data/index.html>) because we believe that players from the same team face similar competition schedules, training plans, and also have very similar dietary habits. Therefore, we think selecting data from the same team will eliminate a significant number of irrelevant variables. After reviewing the transfer records of the Premier League in these years (the 2020-21 season, the 2021-22 season, and the 2022-23 season), we found that the rosters of some teams have changed significantly. As a result, we decided to abandon the approach of studying a single team. On the contrary, we began to consider analyzing players as individuals. Since each player comes from a different team, the samples better represent the overall characteristics of the league. Additionally, we believe that the standardization of the Premier League and the differences in competition format can help mitigate some of the variations.

2.2. Data preprocessing

In this section, we briefly describe the data sets we used and tools in our football analysis. In order to make the research more time-sensitive, we choose the football player from the FA Premier League whose player's time on the court ranked in the top twenty in each of the three seasons: the 2020-21 season, the 2021-22 season, and the 2022-23 season. In the Premier League, there are a number of substitute players whose playing time, match appearances, and performance data are too limited to be included in our analysis.

To avoid incorporating data from these players, we will focus on statistical analysis of the top twenty players with the highest playing time in each season. This approach ensures that our sample consists of players who have had significant contributions on the field, providing a more reliable dataset for our study.

In the course of further research on the data of these players, we found that a portion of these players are goalkeepers. We began to re-evaluate the purpose and practical significance of our research. We hope that our research can have universality and be applicable to most players, due to the different movement patterns and training methods of goalkeepers compared to most other players [1]. Goalkeepers typically possess a greater height compared to players in other positions. In our research sample, we found that goalkeepers are indeed represented among the taller individuals. We decided to remove this part of the goalkeeper's data.

As we delved deeper into the data, we discovered that a few players presented special cases: some ranked among the top twenty in playing time for a particular season across all Premier League players. While this allowed these players to be included in our analysis, unforeseen circumstances, such as severe injuries, caused them to miss a significant number of matches over the past three years. For example, Stuart Dallas from Northern Ireland ranked seventh in playing time during the 2020-2021 season in the Premier League (this ranking includes goalkeepers), with a total of 3,410 minutes on the pitch. However, he suffered a leg fracture during a match against Manchester City in 2022, which significantly impacted his career, ultimately leading to his retirement in 2024. To avoid the influence of these data points on our analysis, we decided to remove these players from the dataset. This will help ensure the accuracy and reliability of our results.

2.3. Quantitative strategy

The next issue we face is how to quantify the injury risk of football players. To enhance the practical significance of our research, we decided to quantify the injury risk of players by measuring the number of days they miss due to injuries. In the following article, we will use match-loss to replace the number of matches missed by players due to injury. This metric will help us better understand the health status of players throughout the season and analyze factors related to injuries. By doing so, we can more accurately assess the injury risks of different players and their potential impact on team performance. At the same time, for the team, both the manager and the fans are more concerned about whether players will miss the next match. During our research, we also discovered that some players experience minor injuries, which might persist for two to three days. Interestingly, despite these injuries, many of these players choose to continue participating in matches rather than sitting out.

2.4. Data analysis

After completing the data preprocessing work, we began analyzing the data. We conduct OLS regression analysis on the basic variables: age, weight, and height.

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OLS Regression Results
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Dep. Variable:      match-loss      R-squared:      0.003
Model:             OLS              Adj. R-squared: -0.017
Method:            Least Squares   F-statistic:    0.1310
Date:              Fri, 27 Sep 2024  Prob (F-statistic): 0.719
Time:              20:39:56      Log-Likelihood: -214.67
No. Observations: 53              AIC:            433.3
Df Residuals:     51              BIC:            437.3
Df Model:          1
Covariance Type:  nonrobust
=====
              coef      std err      t      P>|t|      [0.025      0.975]
-----
const      -3.3743      50.122     -0.067   0.947    -103.998    97.250
height      0.0895       0.275      0.362   0.719     -0.452     0.651
=====
Omnibus:          6.149      Durbin-Watson: 1.626
Prob(Omnibus):   0.046      Jarque-Bera (JB): 6.107
Skew:            0.791      Prob(JB):       0.0472
Kurtosis:        2.485      Cond. No.       4.70e+03
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Figure 1. Height Ols regression

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OLS Regression Results
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Dep. Variable:      match-loss      R-squared:      0.002
Model:             OLS              Adj. R-squared: -0.017
Method:            Least Squares   F-statistic:    0.1235
Date:              Fri, 27 Sep 2024  Prob (F-statistic): 0.727
Time:              18:27:04      Log-Likelihood: -218.24
No. Observations: 54              AIC:            440.5
Df Residuals:     52              BIC:            444.5
Df Model:          1
Covariance Type:  nonrobust
=====
              coef      std err      t      P>|t|      [0.025      0.975]
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const       8.2170      18.558     0.443   0.660    -29.022    45.456
weight      0.0864       0.246     0.351   0.727     -0.407     0.580
=====
Omnibus:          6.257      Durbin-Watson: 1.640
Prob(Omnibus):   0.044      Jarque-Bera (JB): 6.308
Skew:            0.805      Prob(JB):       0.0427
Kurtosis:        2.538      Cond. No.       734.
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Figure 2. Age Ols regression

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OLS Regression Results
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Dep. Variable:      match-loss      R-squared:          0.001
Model:              OLS              Adj. R-squared:     -0.021
Method:             Least Squares     F-statistic:        0.03574
Date:               Fri, 27 Sep 2024    Prob (F-statistic): 0.851
Time:               20:41:27          Log-Likelihood:     -195.35
No. Observations:   48              AIC:                394.7
Df Residuals:       46              BIC:                398.5
Df Model:           1
Covariance Type:    nonrobust
=====
                    coef    std err          t      P>|t|    [0.025    0.975]
-----
const             18.1399    17.506         1.036     0.306    -17.098    53.378
age                -0.1260     0.666        -0.189     0.851     -1.467     1.215
=====
Omnibus:           5.962    Durbin-Watson:      1.621
Prob(Omnibus):     0.051    Jarque-Bera (JB):   5.772
Skew:              0.798    Prob(JB):           0.0558
Kurtosis:          2.421    Cond. No.           220.
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Figure 3. Weight Ols regression

We conducted an OLS regression analysis using players' height, age, weight, and the number of match-loss. Figure 1 shows that the R-squared of height and match-loss is 0.003(0<R-squared<1). Combined with other data, it also shows that a player's height does not have much to do with injury risk. As shown in Figure 2, the R-squared of age and match-loss is 0.001(0<R-squared<1). Similarly, we cannot conclude that there is a significant correlation between a player's age and injury risk. and the R-squared of weight and match-loss is 0.002(0<R-squared<1) (see Figure 3). These analysis results indicate that the players' weight [2,3], height, and age have little correlation with match-loss.

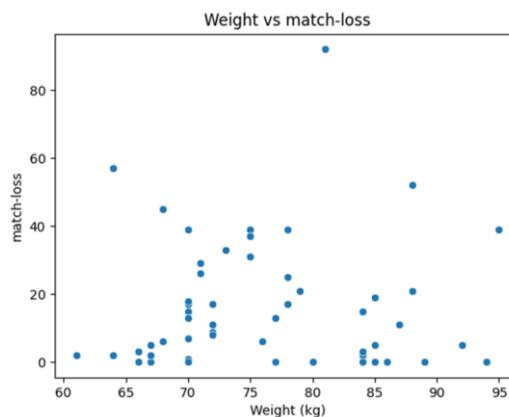


Figure 4. Visualization of weight and match-loss

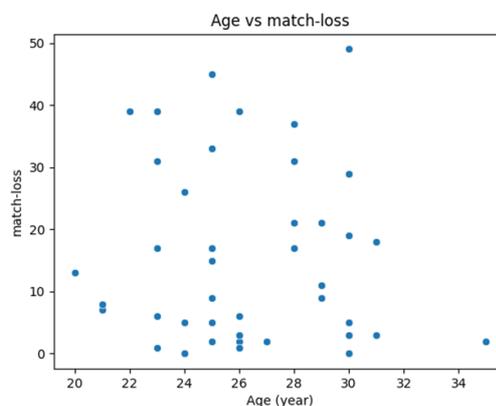


Figure 5. Visualization of age and match-loss

To further validate that age and weight do not correlate to a certain extent for a player's athletic risk, we visualized individual data samples. Figure 4 shows there was no linear or other correlation between the distribution of data between age and the player's injury risk. As shown in Figure 5, there is also no clear indication of age and athletic risk in players, suggesting a strong correlation between player's age and injury risk.

3. Interpretation of the data results

Then, we visualized the data on weight, age, and match-loss and found that neither shows any correlation with match-loss. This also indirectly confirms our previous data analysis results.

We began to reflect on why our previous assumption that the players' basic data and match-loss were related was incorrect. For football players, various physical attributes are indeed important factors. However, injuries often occur when players engage in particularly risky actions. Thus, we shifted our focus to analyzing player behavior rather than their physical attributes [4]. We began to consider whether there is a standardized assessment or metric for analyzing overly dangerous movements in football players.

Therefore, we thought about analyzing the number of yellow cards received by football players. We also concluded that the number of ground duels and aerial duels in football can also serve as indicators to assess the risk associated with the sport. This time, to more intuitively illustrate the relevant analytical results, we used the heat map to represent the relationship between various variables and match-loss.

In this picture, tackle total refers to the player's total number of sliding tackles in three seasons (the 2020-21 season, the 2021-22 season, and the 2022-23 season). Tackle average refers to the average number of sliding tackles per game.

Quantity yellow refers to the player's total number of yellow cards in three seasons (the 2020-21 season, the 2021-22 season, and the 2022-23 season). Average yellow refers to the average number of yellow cards per game. Head refers to the number of header confrontations. And ground refers to the total number of ground confrontation.



Figure 6. Heatmap of the variables

Figure 6 shows that the number of yellow cards, the average number of yellow card per game, header confrontation and ground confrontation are highly correlated with the injury risk of players [5].

Table 1. Correlation analysis and t test of header and ground confrontation on injury risk

	Correlation	P value
Ground	0.448162	0.01986
Head	0.366320	0.01878

After that, we conducted a t-test on the ground confrontation and header confrontation that showed significant results in the heat map. Table 1 shows that our Ground p-value is 0.01986(0.01<p value<0.05) and Head p-value is 0.01878(0.01<p value<0.05). This also validates the results of our previous correlation analysis.

3.1. Player’s age

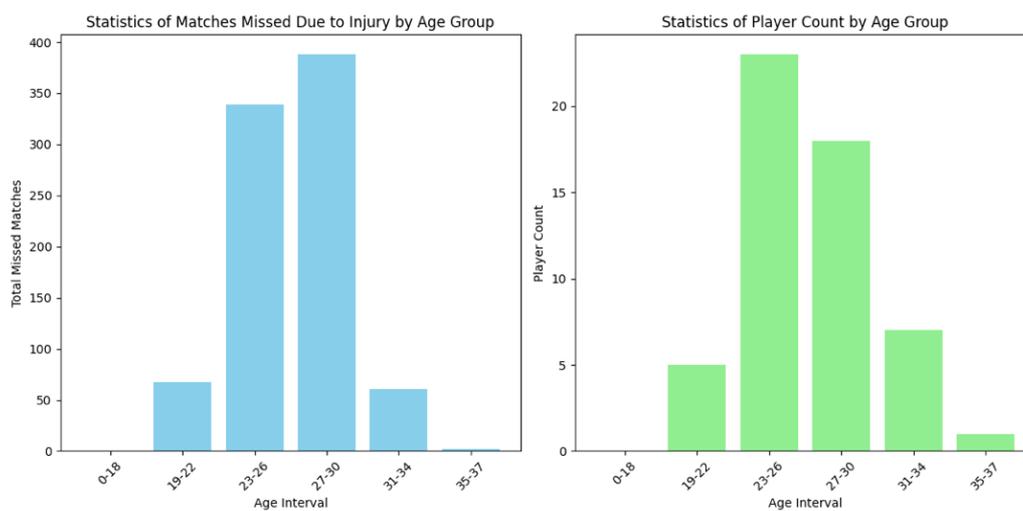


Figure 7. The distribution of the number of players by age group and the total number of injuries by age group in the sample data

Figure 7 shows that height and age have no correlation, the weight and match loss have a weak correlation. Payer’s age and game loss have a weak relation, but it’s still reflecting some facts. Due to the players ' numbers, 23-26 is the biggest, but 27-30 players have the most injuries, and the players between 27-30 have the most probably injuries that lead to match loss [6].

Besides physical conditions, the action in the match is also related to the player’s injuries [7], especially when players are having an aggressive game or having strong physical confrontations.

3.2. Movement of player

The tackle average, tackle total, average Yellow, quantity yellow, head [8], and ground all have different positive levels of correlation with injuries. Compliance with the rules of football is fundamental to ensuring fair play and player safety. The yellow card system, as a key disciplinary measure in the game, is designed to warn players and prevent the repetition of misconduct, thereby maintaining the integrity and flow of the game. Through an in-depth analysis of the patterns and reasons for the issuance of yellow cards in football matches, this paper explores the behaviors that lead to players getting yellow cards and further studies the impact of these behaviors on the process of the game, tactical arrangements, and athletes' individual performance. The overview of the yellow card rules is that according to the regulations of the International Football Federation (FIFA), yellow cards apply to a range of behaviors. This includes but is not limited to, inappropriate behavior, violent

behavior, serious fouls, use of insulting language or gestures, and diving. Yellow cards are issued to warn players to avoid repeated fouls or more serious violations.

3.3. Yellow card

The main reason for getting a yellow card:

3.3.1. Foul play

Foul play is the most common cause of yellow cards. This includes excessive physical contact in the contest for the ball, improper tackles, and pulling on opponents [9].

3.3.2. Improper behavior

Dissatisfaction and protests against refereeing decisions, as well as the use of abusive language or gestures, are also common reasons for yellow cards to be issued.

3.3.3. Tactical fouls

A player may commit a tactical foul in order to interrupt the rhythm of an opponent's attack or to protect their own goal, which is usually also punishable by a yellow card warning. Psychological and social factors behind yellow cards:

Competitive mentality: Athletes' competitive mindset can lead them to adopt riskier behaviors at critical moments.

Team strategy: Coaches' tactical arrangements may sometimes require players to commit fouls to achieve this, which can also increase the risk of yellow cards [10].

Referee's penalty standards: Different referees have different standards of punishment

The main function of yellow cards is to help players, coaches, and referees to manage the game better, reduce unnecessary fouls, and improve the enjoyment and fairness of the game.

A key indicator of overly aggressive defense is a high foul-to-steal ratio. This metric implies that a team's defensive engagements are more likely to be illegal, potentially reflecting a tactic where an inferior team commits deliberate fouls to stall an opponent's attack. To measure this tendency, the number of fouls committed by a team was standardized to calculate the probability that a tackle would result in a foul.

4. Discussion

This study examines the relationship between football players' fundamental physical attributes (e.g., height, weight, age), behavioral factors (e.g., aggression, yellow card frequency), and injury risk. The findings indicate that basic physical characteristics exhibit a negligible association with injury risk. In contrast, a player's average number of yellow cards per game demonstrates a moderate correlation with injury susceptibility. Furthermore, a strong correlation was identified between engagement in ground and aerial duels and an increased risk of injury.

Several data limitations should be noted. The dataset covers the period from 2020 to 2023, which includes the COVID-19 pandemic suspension of the Premier League (March–June 2020). This disruption, along with subsequent health measures, may have affected data collection and player performance. Additionally, variations in athletic intensity and match density arose as players often participated concurrently in other competitions alongside the Premier League. Player mobility, such as transfer to another league after a season of high playtime, also introduces potential data inconsistencies.

To address this challenge, we propose increasing the sample size, as the phenomenon of players participating in other league matches is common in the Premier League. This could help reduce the impact of some irrelevant variables.

We believe that football clubs in different leagues and regions have varying conditions regarding diet, training plans, officiating standards, average attacking intensity, average defensive intensity [11], and tactical strategies. Therefore, we think that future research should focus more on the risk of injuries in other regions, providing scientific guidance for teams and players.

5. Conclusion

In this study, we examined various factors related to football players, including their physical condition, average yellow card occurrences per match, total yellow cards, ground confrontation, and header confrontation, to explore the relationship between these elements and the risk of injury. Our findings indicate that the physical condition of football players has little correlation with injury risk.

Conversely, aspects that reflect the players' on-field behavior demonstrate a certain degree of relevance to the likelihood of sustaining injuries. This suggests that focusing on behavioral metrics may provide valuable insights for injury prevention strategies in football.

References

- [1] Della Villa, F., Mandelbaum, B. R., & Lemak, L. J. (2018). The Effect of Playing Position on Injury Risk in Male Soccer Players: Systematic Review of the Literature and Risk Considerations for Each Playing Position. *American journal of orthopedics (Belle Mead, N.J.)*, 47(10), 10.12788/ajo.2018.0092.
- [2] Kwakye, S.K., Mostert, K., Garnett, D. et al. Risk factors associated with football injury among male players from a specific academy in Ghana: a pilot study. *Sci Rep* 13, 8070 (2023). <https://doi.org/10.1038/s41598-023-34826-0>
- [3] Seow D, Massey A, Correlation between preseason body composition and sports injury in an English Premier League professional football team *BMJ Open Sport & Exercise Medicine* 2022;8:e001193. doi: 10.1136/bmjsem-2021-001193
- [4] Junge, Astrid; Dvořák, Jiri . (2015). Football injuries during the 2014 FIFA World Cup. *British Journal of Sports Medicine*, 49(9), 599–602. doi:10.1136/bjssports-2014-094469
- [5] Arnason, A., Sigurdsson, S. B., Gudmundsson, A., Holme, I., Engebretsen, L., & Bahr, R. (2004). Risk factors for injuries in football. *The American journal of sports medicine*, 32(1 Suppl), 5S–16S.
- [6] Sonesson, S., Lindblom, H., & Hägglund, M. (2023). Higher age and present injury at the start of the season are risk factors for in-season injury in amateur male and female football players—a prospective cohort study. *Knee surgery, sports traumatology, arthroscopy: official journal of the ESSKA*, 31(10), 4618–4630.
- [7] den Hollander, S., & Gouttebarga, V. (2023). Headers and concussions in elite female and male football: a pilot study. *South African journal of sports medicine*, 35(1), v35i1a15236.
- [8] Rinaldo, N., Gualdi-Russo, E., & Zaccagni, L. (2021). Influence of Size and Maturity on Injury in Young Elite Soccer Players. *International journal of environmental research and public health*, 18(6), 3120.
- [9] Rynänen, J., Dvorak, J., Peterson, L., Kautiainen, H., Karlsson, J., Junge, A., & Börjesson, M. (2013). Increased risk of injury following red and yellow cards, injuries and goals in FIFA World Cups. *British journal of sports medicine*, 47(15), 970–973.
- [10] Angoorani H, Najafi S , Sobouti B, Zarei M, Nejati P. The Association of Emotional Intelligence with Sport Injuries and Receiving Penalty Cards Among Iranian Professional Soccer Players. *Asian J Sports Med*. 2020;11(1):e97321.
- [11] Zhao, Y., & Liu, T. (2022). Factors that influence actual playing time: evidence from the Chinese super league and English premier league. *Frontiers in Psychology*, 13, 907336.