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Analyzing Heart Rate Differences and Positional Factors on a Division II Men's Soccer Team

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Abstract

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Men's soccer has various positions, including center backs, outside backs, midfielders, forwards, and goalies. Multiple factors assess their physical performance. **PURPOSE:** The purpose of this study was to better understand the effects of heart rate and other measurable factors on the physical performance of Men's Division II Soccer Athletes. We hypothesize that there is a relationship between players within the same positions on the soccer team having similar heart rate responses, and we assessed the progression of baseline measurement values. **METHODS:** Data was collected using Polar H10 heart rate monitors and Polar applications. There were multiple baseline measurements assessed approximately 16 weeks apart for the off-season and in-season programs. The completed measurements were BIA, Sit-and-Reach Tests, and the Cooper 1.5 Mile Run Test. A two-tailed t-test and ANOVA were used to find the level of significance. **RESULTS:** In the baseline measurements, statistically significant differences ($p<0.05$) were found for the BIA results of Fat %, Fat Mass (lbs), TBW (lbs), and TBW % in the off-season and in-season. Tukey HSD Tests were also assessed for positional differences. For the heart rate, ANOVA significant differences ($p<0.05$) were found for all position heart rate averages in the off-season and in-season. Tukey HSD Tests found significant differences ($p<0.05$) for almost all positions' average heart rate comparisons. **CONCLUSIONS:** Positional heart rate averages for each activity showed significant differences between positions in the ANOVA Test, so we can conclude the heart rate response to the training stimulus wasn't the same for every position.

Key Words: Aerobic, Clusters, Polar, Predictions, Stimulus

Introduction

Heart rate in endurance activities has been widely assessed in many areas, including soccer. A previous study looked into the implications of heart rate variability in perceived physical fitness (Ravé et al., 2020). However, there is little available evidence to suggest what the effects of particular positions can have on the heart rate of these individuals. We hypothesize that players within the same position may have similar heart rate responses due to their similar training profiles. However, players outside of their positions should have differing heart rate responses to training stimuli. If that is the case, there should be a significant difference in the average heart rates over a semester and within individual training sessions.

We further propose the observable predictability of heart rate using time series analysis, assessing whether the correlation between certain factors, such as training session type, position, baseline measurements, and more, contributes to a given heart rate response from an individual. The time series analysis will allow individuals to understand the seasonal implications of high-intensity and low-intensity training stimuli and what heart rate response could potentially be expected.

As this study did not involve a control, we will not refer to this study as an experimental study but an explanatory study, investigating the causative factors that are influencing the heart rate of these individuals, along with correlations that would suggest it. There were no specific control groups to assess the difference, but rather a difference between the beginning and end of the season. However, due to the observational nature of the study on the soccer team in coaching, the researchers didn't influence training methodology for any individual groups. We assume for this study all subjects would have experienced the same general stimulus on their training days without noticeable differences. With these assumptions, in this study we assess the differences in responses of these subjects due to the inherent differences in positions under the same presumed movement stimulus.

Methods

Players were assessed in standard baseline measurements relating to the general components of fitness. These measurements were the BIA, Cooper 1.5 Mile Run Test, Sit-and-Reach Test, Vertical Jump Test, t-test, and 10-Yard Dash Test. The body composition analysis using the BIA scale was recorded following recommended dietary, exercise, and hydration guidelines, "...participants were instructed to (1) abstain from exercise on the day of the visit, (2) fast for 4–5 h prior to their visit and (3) not void their bladder for at least 2 h before the visit" (Randhawa et al., 2021). The Cooper 1.5 Mile Run Test was performed using a stopwatch and a tracking sheet for the athletes with the mapped out 1.5 miles on the field. The Sit-and-Reach Test was performed using the traditional Sit-and-Reach box. The vertical jump test was performed using the Vertec vertical jump device. The t-test was performed using cones lined in the 10-yard base with the width of the T being 10 total yards and timing with a respective stopwatch. The 10-yard dash test was performed using cones measured out 10 yards and then timed with a stopwatch. These baseline measurements allowed for a general understanding of the relative fitness levels of these individuals. These measurements were gathered at the beginning and end of each season (approximately 16 weeks). Due to constraints, not all measurements were successfully gathered for each subject. Therefore, the primary analysis was focused on those successfully collected at the beginning and end of the semester. Also, heart rate data during the 16 weeks was collected using Polar H10 Heart Rate Monitors. These monitors tracked heart rate at two-second intervals. Two sections of sixteen weeks of data were collected, with samples of 33 total subjects (off-season in Spring 2024) and 55 total subjects (in-season in Fall 2024).

In each training session, labels were created relating to the session type as “Small-Sided”, “Game”, “Technical”, and “Conditioning”. “Small-Sided” refers to practices with games such as 3v3, 4v4, 5v5, 6v6, etc., except for 11v11. “Game” refers to practices or games with 11v11 in it. “Conditioning” refers to practices that include conditioning exercises or fitness tests. Finally, technical sessions include practices that were specifically designed to be light intensity and included passing patterns and light technical skill work.

The data analysis was performed in Python 3.12.7 using the Statsmodels, Numpy, Pandas, Sklearn, Seaborn, Matplotlib, and Scipy packages. In the statistical significance part of the study, multiple tests were assessed to determine the significance between individuals, groups, or more. A t-test was performed to determine the difference between the beginning and end of the semester for each body composition metric in the BIA data collection. Second, an ANOVA was computed to determine the positional differences in the baseline measurements. Third, a Tukey HSD test was performed to compare the means for each position in the baseline measurements and to understand where the specific positional differences lay. Finally, we performed Cohen's D Effect Size to understand the general effect of the difference in these baseline measurements across the semester for the beginning and end.

The average heart rates were compared across the different semesters by position across the entire semester and the individual dates. We also showcased the weekly distributions to understand the variability of the data throughout a week for each position in the average heart rate.

The first test performed was a t-test of the first and last 10 average heart rate sessions. The next was an ANOVA of average heart rate differences for position and then the next player. Furthermore, the Tukey HSD test was used to compare the means across positions of the semester. “Multiple comparison methods are used to investigate differences between pairs of population means. In specific it investigates differences between subsets of population means using sample data…The Tukey HSD test analyzes all pair wise comparisons among means” (Nanda et al., 2021).

In the cluster analysis, session types were used to determine the average heart rate per type of session. The variability of those values was also assessed. Furthermore, we looked into the heart rate clusters that could be created using the K-Means elbow clustering method. “Clustering allows finding and analyzing groups that are formed naturally, instead of defining groups prior to looking at the data. The K-Means algorithm is one of the most popular clustering algorithms that belongs to the unsupervised learning techniques. It aims to find the optimum way to group given data, based on the feature similarity of the observations, with the number of groups represented by the variable K that is given as input” (Tselentis & Papadimitriou, 2023). “A way to determine the number of clusters beforehand is by running the K-Means algorithm several times and comparing the results. To compare the results across different values of K, a popular metric is the mean distance between cluster centroids and the data points assigned to each one of them, which decreases as the number of clusters is increased. When this metric is plotted as a function of the number of clusters K, the “elbow point”, where the rate of this metric’s decrease sharply shifts, is revealed together with the corresponding number of clusters K” (Tselentis & Papadimitriou, 2023). First, we determined an average heart rate cluster and then showcased when a position was within that cluster. The average heart rate for that cluster group of that position was also determined. Also, the baseline measurements were put into cluster groups based on certain average values.

With predictive analysis, a time series determines if any seasonal factors or other behaviors were present in the training data. Generally, this is very dependent on the training stimulus set out by the coach during the season. However, it is interesting to understand the expected cyclical factors that can be showcased in intensity from high intensity to low intensity. In the time series analysis, seasonal decompositions were assessed based on the average heart rates of each position and all participants for the off-season and the in-season separately. Furthermore, ARIMA modeling was assessed to determine the specific predictability that would be possible based on some of these factors. "The ARIMA model was recommended by Box and Jenkins. It is a time series forecasting model and its general form is as follows: (p, d, q), where p and q represent the orders of auto-regressive (AR) and moving average (MA), respectively, while d represents the order of the differences" (Singh et al., 2023). The AIC and BIC were used to determine the effectiveness of different potential models to choose an optimal (p, d, q) with the lowest AIC and BIC for all chosen potential combinations. This was similarly used in determining an optimal Sarima Model to choose an optimal (p, d, q, P, D, Q, s). Where (p, d, q) are the same as above, and the (P, D, Q, s) relate to the seasonality of the original (p, d, q).

Results

The first tests performed related to the individual body composition metrics collected by the BIA. In this analysis, we found significant differences ($p < 0.05$) for the off-season beginning vs. end in Fat % ($p = 0.01559$), Fat Mass (lbs) ($p = 0.04891$), TBW (lbs) ($p = 0.01720$), and TBW % ($p = 0.00802$). For the in-season, significant differences were found in Weight (lbs) (p <

0.00001), Fat Mass (lbs) ($p = 0.01495$), FFM (lbs) ($p < 0.00001$), Muscle Mass (lbs) ($p < 0.00001$), TBW (lbs) ($p < 0.00001$), Bone Mass (lbs) ($p = 0.00114$), BMI ($p < 0.00001$), and Sit-and-Reach Test ($p < 0.00001$). For the positional differences of the baseline measurements, an ANOVA was performed. In the off-season, there were no significant positional differences. However, in the in-season, there were multiple ANOVA significant positional differences including Weight (lbs) ($p = 0.01703$), FFM (lbs) ($p = 0.00675$), Muscle Mass (lbs) ($p = 0.00685$), TBW (lbs) ($p = 0.01964$), and 1.5 Mile Run Test ($p = 0.04876$). Finally, in the in-season program, there were multiple Tukey HSD Test comparisons of mean differences in baseline measurements between positions. For the FFM (lbs) and Muscle Mass (lbs), there were significant differences ($p < 0.05$) between these positions: Center Back and Forward, Center Back and Outside Back, Forward and Goalie, Goalie and Outside Back. Now, for Cohen's D Effect Size, it was calculated for the difference in the measurements between each collection of data. Notable measurements were showcased for the off-season beginning vs. end and the in-season beginning vs. end. For the off-season, Weight (lbs) = 0.18723, Muscle Mass (lbs) = 0.10058, Fat % = 0.32702. For the in-season, Weight (lbs) = -0.13398, Muscle Mass (lbs) = -0.15302, Fat % = -0.04481.

Next, an analysis was performed on the heart rate values. The averages were taken across the 16-week program in-season and off-season for each position. Below are graphs relating to the daily and weekly distributions of these values.

Figure 1: This figure includes the average heart rates by position along with the team average across the off-season training program. This showcases the individual training session dates on a line plot.

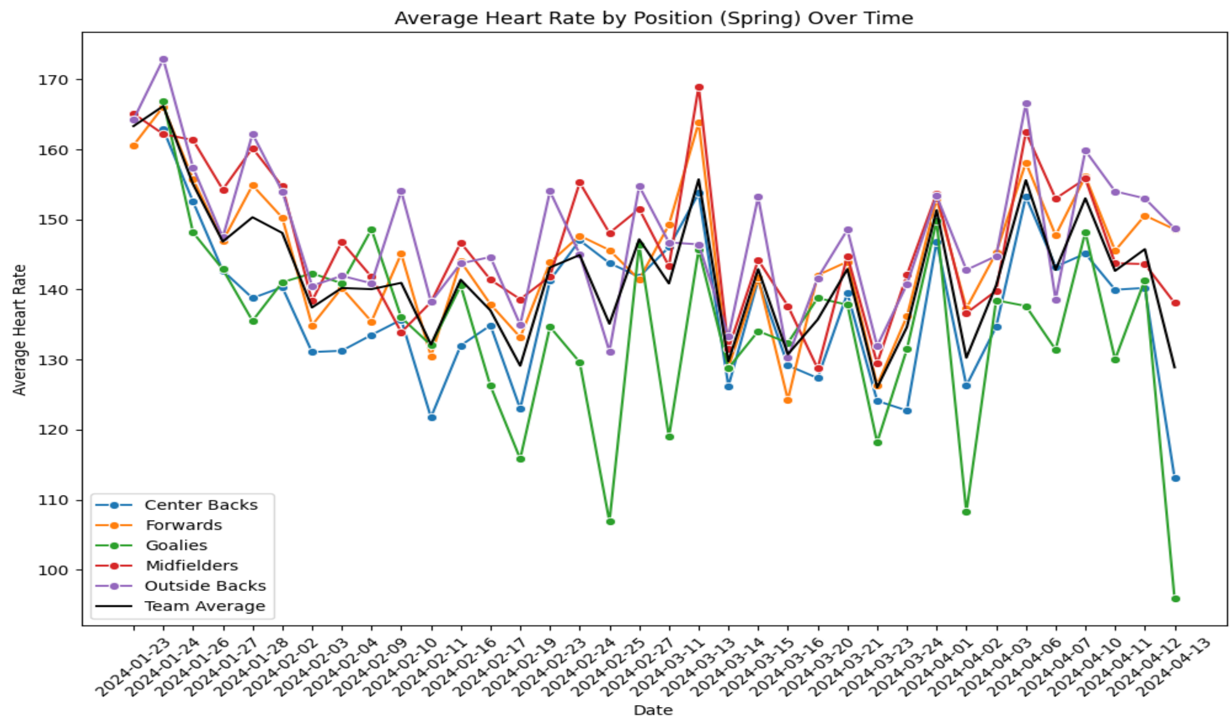


Figure 2: The weekly box plots across the off-season training program are labeled for the different positions with their average heart rates from each training session of all players in that week of the year.

Figure 3: This figure includes the average heart rates by position along with the team average across the in-season training program. This showcases the individual training session dates on a line plot.

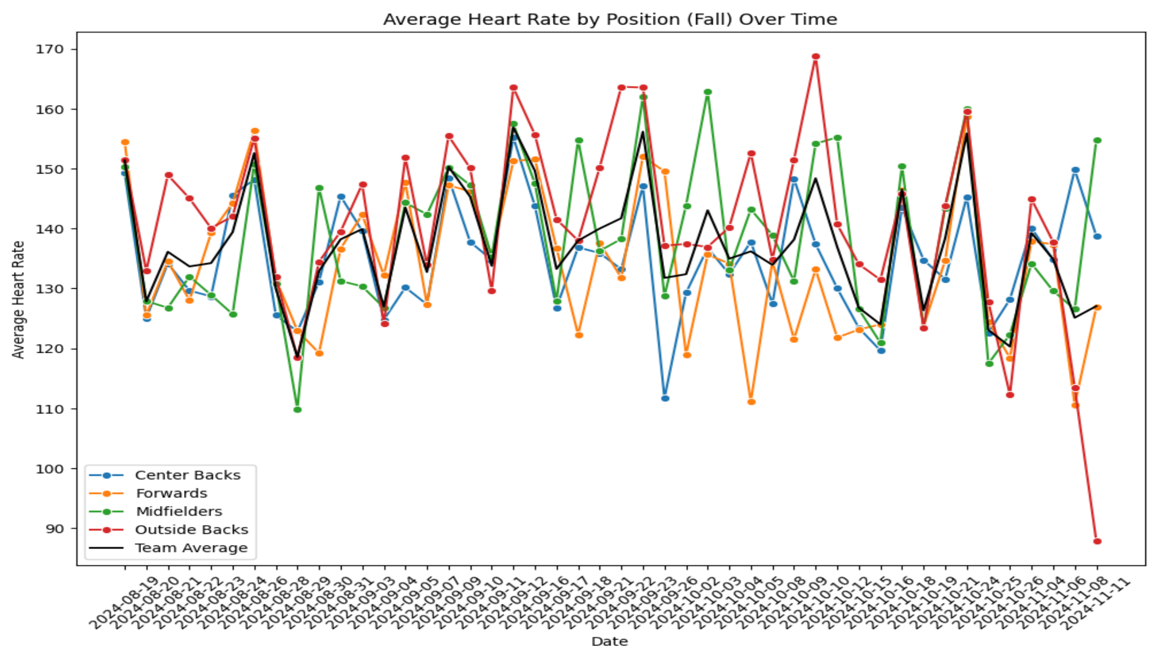
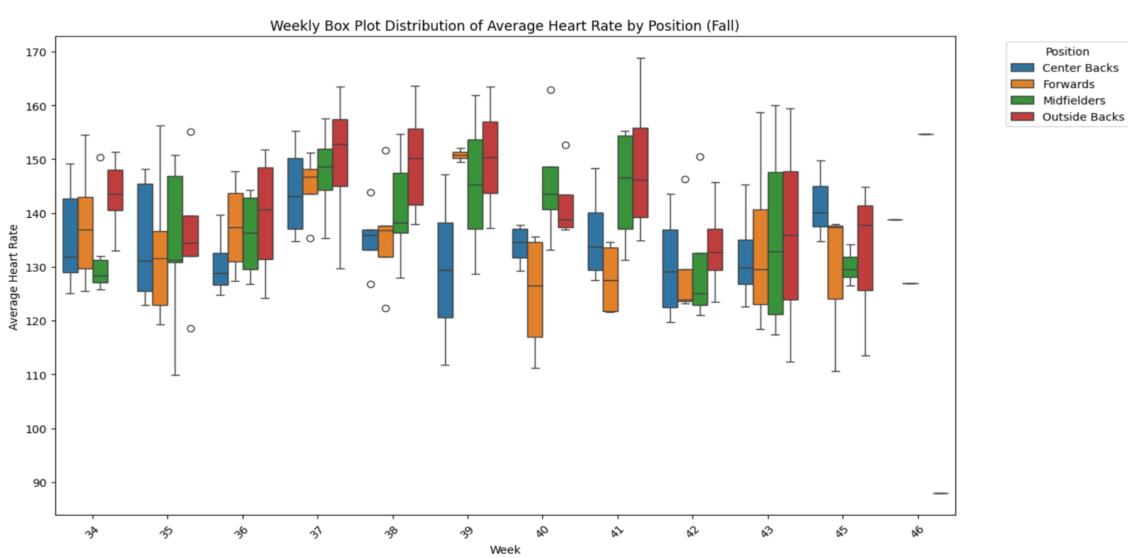


Figure 4: The weekly box plots across the in-season training program are labeled for the different positions with their average heart rates from each training session of all players in that week of the year.



Furthermore, t-test differences were calculated between the first 10 and last 10 session averages of the time for each semester. In both cases, the averages weren't statistically significant. Then, an ANOVA analysis was conducted to determine the positional differences in the averages across the off-season and in-season separately. In the off-season and in-season, ANOVA results were $p < 0.00001$. After taking the ANOVA into account of all positions, the Tukey HSD Test looked at a comparison of means for each position to understand the specific positional differences that might be present in the heart rate averages. In all positional comparisons, there were significant differences except for one instance in the in-season relating to Center Backs' and Midfielders' average heart rates. Otherwise, each position was significantly different ($p < 0.05$) in their comparison of means across the semester.

For the clustering analysis, we first interpreted the average heart rate for each type of session. For the off-season, Small Sided: 144 bpm, Technical: 143 bpm, Conditioning: 159 bpm, and Game: 139 bpm. For the in-season, Small Sided: 141 bpm, Technical: 129 bpm, and Game: 134 bpm. Then, the variability in the heart rate was assessed theoretically for the off-season and the in-season through standard deviation computation. For the off-season, Small Sided: 29 bpm, Technical: 26 bpm, Conditioning: 29 bpm, and Game: 33 bpm. For the in-season, Small Sided: 29 bpm, Technical: 26 bpm, and Game: 36 bpm.

Baseline measurements were used for further clustering as well. Here is the beginning of the in-season analysis to showcase the clustering that was effective:

Table 1: This includes the values that are found in the K-means clustering method for the beginning of the in-season training program baseline measurements. There are three clusters assessed for the baseline measurement values.

Clusters and Measurements In-Season			
Measurement Clusters	**Cluster 1**	**Cluster 2**	**Cluster 3**
Height (in)	70.86	71.90	67.89
Age (yrs)	19.59	20.50	19.22
Weight (lbs)	160.05	189.04	136.27
Fat %	12.28	16.73	10.13
Fat Mass (lbs)	19.70	31.66	13.98
Muscle Mass (lbs)	133.34	149.62	116.16
TBW %	61.38	57.35	64.63
BMI (kg/m^2)	22.42	25.74	20.84
1.5 Mile Run Time (minutes)	9.56	10.33	9.62
Sit-and-Reach (cm)	34.29	35.75	39

The positions associated with these clusters included: Center Backs cluster 1 = 3, cluster 2 = 3, cluster 3 = 0; Forward cluster 1 = 9, cluster 2 = 1, cluster 3 = 4; Goalie cluster 1 = 2, cluster 2 = 2, cluster 3 = 0; Midfielder cluster 1 = 6, cluster 2 = 4, cluster 3 = 2; Outside Back cluster 1 = 9, cluster 2 = 0, cluster 3 = 3. This helps to understand the layout of individuals within their respective positions.

After all the clustering, there were predictive methods assessed in time series data. Here is a sample seasonal decomposition performed on the midfielders' average heart rates of the off-season program. Following that are the ACF and PACF plots along with the ADF test to determine the order of differencing:

Figure 5: This figure showcases a seasonal decomposition of the off-season program, labeling the original average heart rates of the team along with the smooth trend line, seasonal factors, and residual values.

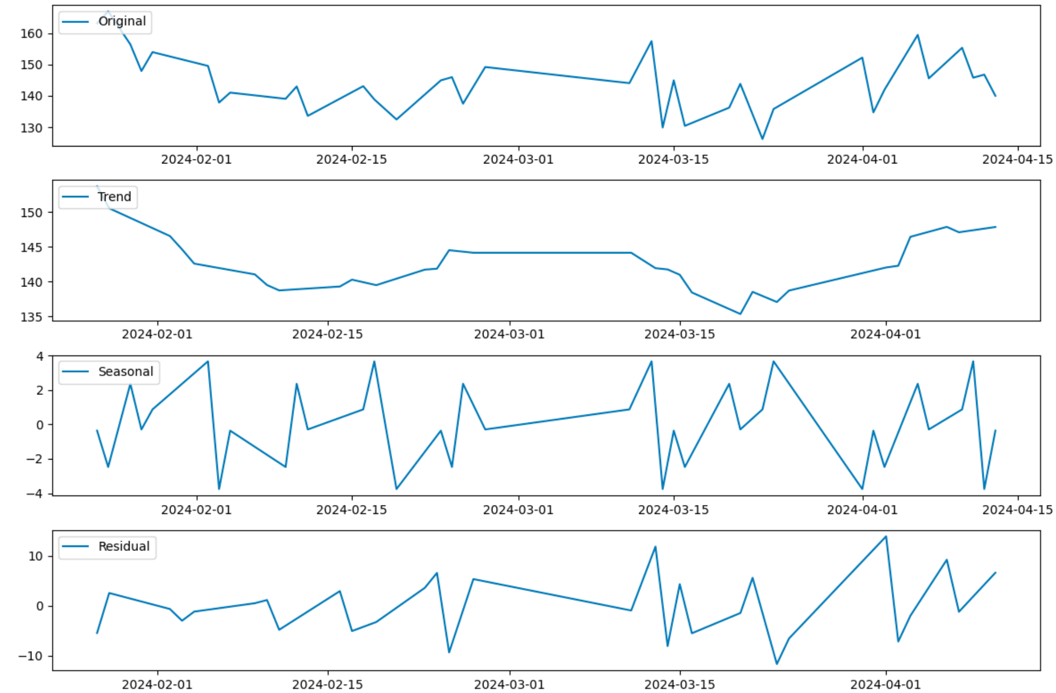


Figure 6: This figure showcases the ARIMA model for the off-season program team average heart rate. The appropriate ARIMA model for this data was (0, 0, 3) with Mean Squared Error (MSE): 53.06371325673898, Root Mean Squared Error (RMSE): 7.284484419417683, Mean Absolute Error (MAE): 5.875127265389121.

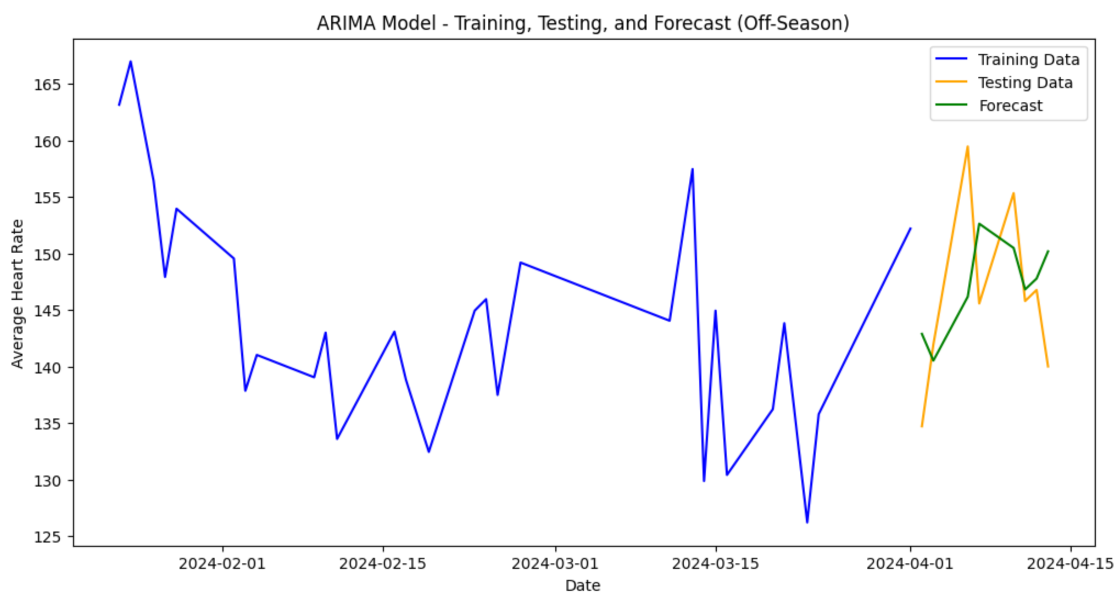
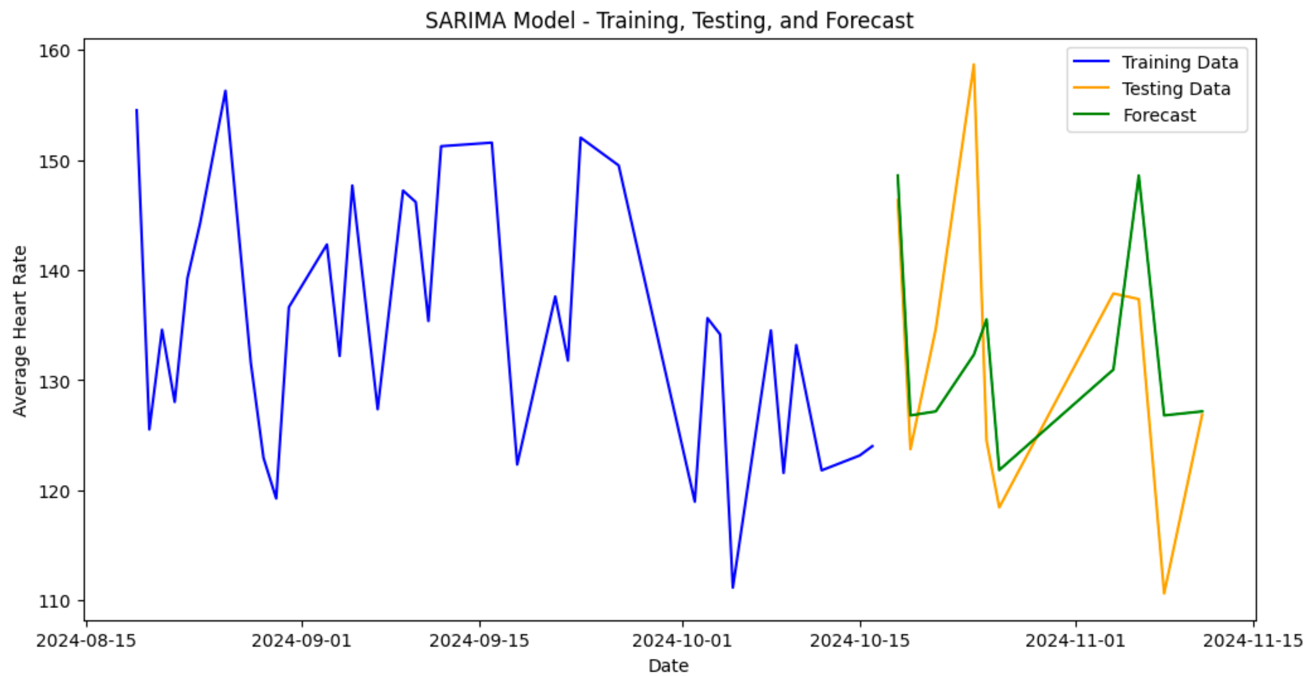


Figure 7: This figure showcases the SARIMA model for the in-season training program forwards average heart rate. Mean Squared Error (MSE): 133.4439267702052, Root Mean Squared Error (RMSE): 11.551793227469282, Mean Absolute Error (MAE): 8.819282947908066.



The two models above with the figures were the best performing models for any group in the off-season and in-season programs, respectively.

Now, there were more ARIMA (p, d, q) and SARIMA (p, d, q, P, D, Q, s) models performed that weren't as needed to showcase graphically, but still showcased optimal results that should be reported for the (p, d, q) and AIC and BIC criteria. First, the results of the off-season include: team average heart rate with ARIMA Model (0, 0, 3) and AIC = 259.64 and BIC = 267.56; outside backs with SARIMA Model was (0, 1, 3, 0, 1, 1, 7) and AIC = 224.46 and BIC = 231.12; forwards with SARIMA Model (1, 0, 0, 1, 1, 0, 7) and AIC = 232.92 and BIC = 237.02; midfielders with ARIMA Model (2, 0, 2) and AIC = 269.35 and BIC = 278.85; center backs with ARIMA Model (4, 0, 5) and AIC = 262.04 and BIC = 279.46. Next, the results of the in-season include: team average heart rate with SARIMA Model was (0, 0, 0, 1, 1, 0, 7) and AIC = 303.56 and BIC = 306.89; outside backs with SARIMA Model (0, 0, 1, 0, 1, 1, 7) and AIC = 337.51 and BIC = 342.50; forwards with SARIMA Model (0, 0, 0, 0, 1, 1, 7) and AIC = 319.18 and BIC = 322.51; midfielders with SARIMA Model (3, 1, 3, 0, 1, 1, 7) and AIC = 319.57 and BIC = 332.68; center backs with SARIMA Model (0, 0, 5, 2, 1, 0, 7) and AIC = 299.85 and BIC = 313.16.

Discussion

There are some limitations in the study regarding the varying genetic heart rates. Extreme maximum heart rate values were found in certain individuals that would skew the average heart rate results for their given positional groups. Furthermore, there were instances where the researchers couldn't be sure that the monitors were accurately tracking the heart rate of the individuals. As subjects wore the monitors, sometimes they wouldn't be correctly attached to the chest region. Values could be inappropriately read without direct contact. Furthermore, with the field equipment available for the study, it was hard to determine the accuracy of the maximum heart rates. Another limitation regarded players sitting on the sidelines for the entirety of the game. In most instances, these data collections were taken out of the study, but there may be some that were missed, which could reduce the accuracy of the average heart rates during exercise periods. Further limitations regarding the baseline measurement collection referencing body composition values from the BIA Scale are possible. Some individuals may have failed to follow the proper protocol regarding diet, hydration, and exercise status in the time leading up to the test. Generally, the implications don't appear to be extremely harmful to the data collection as in this study, "Our findings suggest that in our sample, acutely violating the preliminary measurement BIA assumptions does not significantly impact the derived %FM and impedance values" (Randhawa et al., 2021).

The games were more variable in heart rate compared to other types of sessions due to the increased rest periods for some individuals on the sidelines or when the ball is on the other side of the field. However, Conditioning had a very large average heart rate with low heart rate variability, indicating that these sessions would be the most intense. Furthermore, there were distinct cluster groups that could be found for the different positions in baseline measurements and heart rate response. Finally, the baseline measurements generally showcased improvements in values in the off-season regarding Fat %, Muscle Mass (lbs), etc. However, the in-season didn't showcase as positive of implications in the difference of these values using Cohen's D Effect Size.

Next, the statistical tests that were performed to understand the statistical significance indicate that there was indeed a significant difference in the average heart rate for each position. These findings were found using the ANOVA across all positions, and also an individual comparison of the average heart rate for each position using the Tukey HSD test.

The time series models show implications that the training stimulus in the off-season was more predictable in terms of the ARIMA models that were used, showcasing a vast difference. This could be due to the unpredictability of training stimuli during the in-season time period, as players will also move in and out of the starting squad, getting different training stimuli. However, during the off-season, the training is relatively consistent for all individuals. Therefore, we can also see this in the average heart rate for each position as the off-season shows adaptability, and the in-season shows more of a parabolic output.

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Conflicts of Interest

The results of the study are presented clearly, honestly, and without fabrication, falsification, or inappropriate data manipulation. The results of the present study do not constitute endorsement by the American College of Sports Medicine. There are no outstanding conflicts of interest.

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