Physical Strength & Fear-Related Personality

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Abstract: Psychology plays an integral role in understanding human behavior and humanity at large. Sometimes, there can be hidden connections between an individual's psychological makeup and other attributes of their character that can be enlightening once uncovered. In this study, we investigate the relationship between fear-related personality traits and physical strength, with a specific focus on grip strength, in a diverse sample of undergraduate students from five U.S. universities. Leveraging the HEXACO personality model, the research aims to understand the influence of fearfulness, anxiety, emotional dependence, and sentimentality on both psychological and physical well-being. The methods involve the analysis of a dataset from Kaggle, employing regression, classification, and clustering techniques to integrate personality scores and grip strength metrics. While regression and classification models show limited predictive capabilities, clustering techniques yield valuable insights. Notably, fear-related personality traits emerge as predictors of overall physical strength, with higher trait levels correlating with lower grip strength. The study underscores the importance of emotional personality traits in revealing variations in physical strength, offering implications for personalized mental health interventions.

Keywords: Psychology; HEXACO; Personality; Grip Strength; Physical Strength

1. Introduction

Traits along the emotionality dimension of personality, including fearfulness, anxiety, emotional dependence, and sentimentalism, play a significant role in shaping an individual's psychological landscape. Understanding the interactions between these traits not only sheds light on the complexities of human behavior but also provides insights into how they might influence both an individual's mental and physical well-being.

Fearfulness, an emotional response triggered by the anticipation of potential threats, including the prospect of pain and danger, is closely linked with anxiety. Those predisposed to fearfulness may encounter heightened levels of anxiety, giving rise to various psychological and physiological effects. Anxiety, characterized by an overwhelming sense of worry and restlessness, frequently manifests in symptoms such as muscle tension, which can adversely affect an individual's overall physical well-being.

Emotional dependence is a trait marked by reliance on others for emotional support and validation. Those with high emotional dependence may experience heightened levels of stress in situations of emotional vulnerability. Sentimental individuals tend to attach deep emotional value to experiences and possessions. These traits, such as heightened sensitivity to threats or a tendency to experience fear more intensely, can contribute to an individual's overall psychological and physical well-being.

The HEXACO model of personality, which consists of six major dimensions- H-Honest-Humility, E-Emotionality, X-eXtraversion, A-Agreeableness, C-Conscientiousness, O-Open to Experience can be integrated to provide a more comprehensive understanding of personality traits [1]. This psychological framework categorizes personality based on those key dimensions using a 5-point scale. A score of 1 typically indicates a low level of the trait, while a score of 5 indicates a high level. The middle point, 3, is often considered neutral or average. The HEXACO model gives us a way to understand different aspects of personality, from how honest and humble someone is, to how they handle emotions, social situations, and new experiences. Each person's unique combination of these traits contributes to their overall personality profile and psychological makeup.

This study aims to uncover potential links between scores across the emotionality dimension of personality and an individual's physical strength, with a specific focus on investigating grip strength. In our dataset, grip strength is measured in pressure units (kg/F), tested by a handheld strength measuring device. In the scientific community, grip is considered to be an essential representation of a person's health and muscular strength. Supporting this, writer David Keisler states, "Some consider testing hand grip strength as another vital sign similar to measuring blood pressure, temperature and pulse rate." [2]. Grip strength serves as a straightforward and convenient measure that provides valuable insights into the overall strength of one's body. Opinions vary on the relationship between fear and physical strength. Some argue that increased fear may correspond to reduced physical strength, while others contend that the interplay becomes more complicated when factoring in gender differences between males and females. The incorporation of gender as a distinct variable indicates the intention to scrutinize and contrast responses based on this specific factor. This approach acknowledges the nuanced nature of the relationship between fear, physical strength, and potential gender-related influences.

The significance of this investigation into the relationship between fear-related personality traits and physical strength could influence the way we approach mental health interventions. Valuable insights may contribute to more effective and personalized approaches to address psychological conditions influenced by temperament and physical well-being. This research could pave the way for broader implications for refining mental health interventions based on a nuanced understanding of the interplay between personality factors and physical health.

2. Materials and Methods -

The dataset "Physical Strength & Fear-Related Personality" was obtained from kaggle.com. The dataset contained 3 different CSV files about physical strength and fear-related personality traits of undergraduate students from 5 different universities.

The programming and coding were conducted on Jupyter Notebook and were visualized on the same platform. Accession and reading of the CSV files with the data was done with the Pandas and NumPy python libraries, as well as for its manipulation and cleaning.

With there being different columns full of HEXACO score features we decided to group and sum these columns amongst individuals across the given row. These group scores were appended to the dataset and given a column name specific to the HEXACO category.

The correlations between the different features within our dataset were calculated using a combination of the grip strength data along with the HEXACO personality score features. Upon combining these features together we stepped into further analysis using a seaborn heatmap which resulted in a visual display of the different correlations seen within our data.

Regression analysis was performed using three different models. Beginning with a Random Forest Regressor, we split the data into a training and testing set. After fitting the model, we then predicted the target variable with the testing set. This was plotted using a scatterplot of actual vs. predicted values to see the accuracy of the random forest regressor. In turn, the mean-squared error (MSE) and R2 values were printed. Next, a bar plot of feature importances was created for the random forest model to visualize the most important feature of the model. This was repeated using the filtered datasets of only males and females.

The implementation of the Ridge and Lasso Regression was done using the split training and testing sets for combined, male, and female datasets. The models were fitted using different alpha values, printing MSE and R2 in turn. The singular Ridge and Lasso models with the lowest MSE and greatest R2 were chosen as the best models.All three regression model MSE and R2 values were put into a table to display all the models together. The model with the lowest MSE and greatest R2 was the most accurate.

After all necessary regression processes were performed on the dataset, we moved on to classify our data to see if we could extract any further useful information. Similarly to the methods of regression, we split the dataset by the gender feature into two datasets of only male and and females. To efficiently perform classification, we decided to implement three classification models and compare their results for each gender separately. These models are random forest classification, logistic regression classification, and bagging classification.

Similarly to the regression process, classification was performed on both male and female split datasets. The process of implementing the three models began with a description of the dataset, along with the setting and implementation of necessary low, medium, and high thresholds. These thresholds were based on statistics of the columns, specifically the low described 25% of columns stats, medium described the 50% of columns stats, and high described the 75% of columns stats. Using these thresholds, both the male and female datasets were grouped into these three sections, allowing for the fitting of classification models on the changed datasets. Later, each model was used to predict the y testing values and were graded based on accuracy and F1 score performances.

To be able to fully understand our dataset, we finalized our methodology by clustering our data. From this, we wanted to see if grouping the dataset would yield any interesting patterns or results. To begin performing our K-means clustering, we first needed to decide on an optimal number of clusters to work with. For this, we plotted an elbow plot with the x-axis representing the K-means results for a range of clusters from 1 to 10 and the y-axis representing the values within the cluster sum of squares for each cluster value individually. This line graph was created for the male, female, and combined datasets. The ideal number of clusters was decided where there was a visible “elbow” bend in the line in the figures.

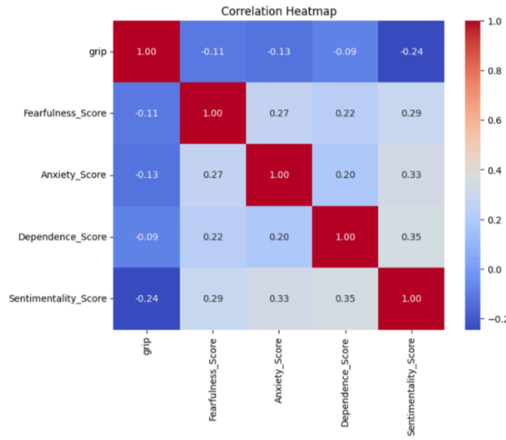
The clustering with the ideal K was performed on each of the four emotional traits. Using the k-means clustering results, scatterplots were created for each of the traits. These graphs plotted a combined score from 4 to 20 for the specific trait on the x-axis and the grip strength of an individual on the y-axis. The points were colored by cluster. Next, the mean grip strength of each cluster was calculated and compared to the total mean grip strength. Conclusions were then drawn from the comparison.

3. Results

3.1. Research Questions Addressed

3.1.1 What correlations exist between HEXACO psychological scores and strength metrics in the dataset?

- The correlation between grip strength and relative HEXACO personality scores was graphically represented, seen in Figure 1.



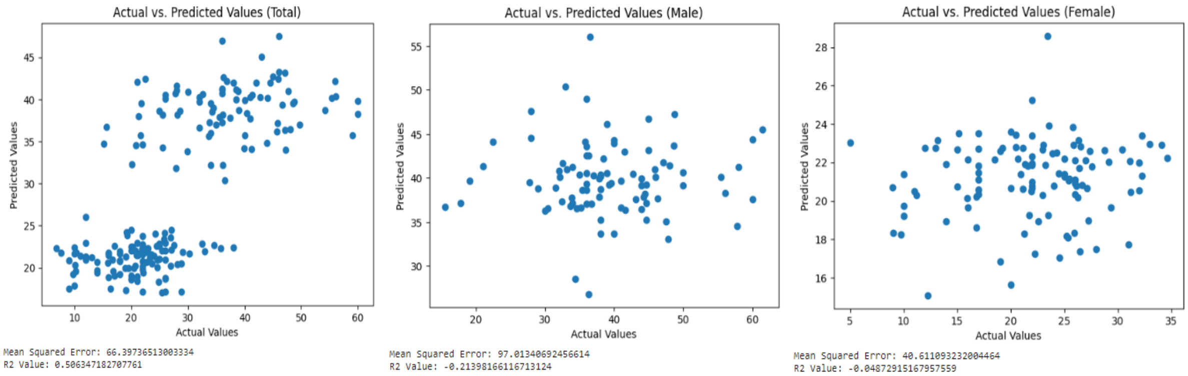
(a)

Figure 1. Correlation heat map representing the relationship between grip strength and relative HEXACO personality trait scores (a) Grip strength in relation to these personality scores appears to have a slight negative correlation, meaning that as HEXACO scores increase grip strength decreases, or vice versa (as grip strength increases, HEXACO scores decrease). HEXACO scores when compared to one another show a positive correlation. This demonstrates the result of a strong psychological score resulting in strong psychological scores across other fields. Seen across the diagonal it is a perfect 1.0 correlation as it is measuring the metric in comparison to itself.

3.1.2. Can we develop a model that accurately predicts grip strength based on personality traits such as fearfulness, anxiety, emotional dependence, and sentimentalism (as measured by the HEXACO personality model)?

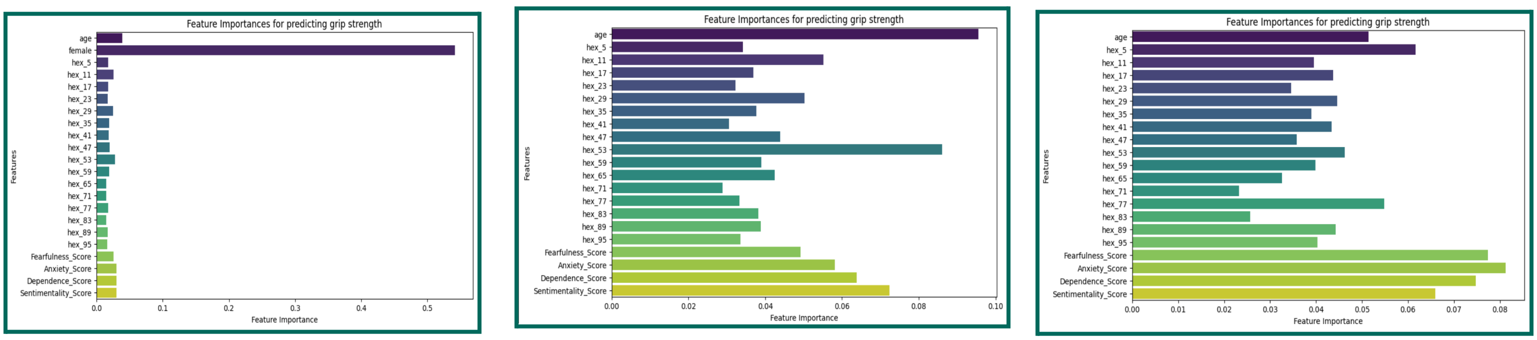
Random Forest Regressor:

- We implemented a total of three regression models on the data (Random Forest, Ridge, and Lasso).
- As shown in Figure 2, the scatterplots for males, females, and both indicate that the Random Forest Regressor models are fairly inaccurate.
- It is expected that the actual and predicted values will form a diagonal straight line, our data points do not form lines.
- Random Forest Regressor models’ performances were poor, with a high MSE and negative or low R2 value (**Figure 2. (a)**, **(b)**, and **(c)**).
- For the combined data, gender is a major feature as opposed to the other features. (Shown in **Figure 3. (a)**).
- For males only, the main features are age and Hex_53 (**Figure 3. (b)**).
- We can see that the four personality traits are the most important features of the female data. (**Figure 3. (c)**).



(a) (b) (c)

Figure 2. Scatterplots visualizing actual vs. predicted values of a Random Forest Regressor. Both male and female (a). Males (b). Females (c).



(a) **(b)** **(c)**

Figure 3. Random Forest Feature Importances. Male and Female (a.). Male (b.). Female (c).

Ridge and Lasso Regression:

- When looking at the Mean Squared Error (MSE) and the R2 value, we can see that the Lasso Regression model is the most accurate for the male dataset. It has the lowest MSE and a greater R2. (**Table 1 (a)** and **Table 1 (b)**)

Model	(Best) Lead Parameter Value	MSE 0 - ∞	R2 -∞ - 1
Random Forest	N_estimators = 400	97.01340692456	-0.21398166116
Ridge Regression	Alpha = 2.0	90.58065658197	-0.13348514842
Lasso Regression	**Alpha = 0.5**	**79.55001801169**	**0.004547246889**

Table 1 (a): Three regression models performed on the male dataset.

Model	(Best) Lead Parameter Value	MSE $0 - \infty$	R2 $-\infty - 1$
Random Forest	N_estimators = 100	40.566516586936	-0.04757801726
Ridge Regression	Alpha = 2.0	40.062765862355	-0.03456930392
Lasso Regression	**Alpha = 0.5**	**39.226156756812**	**-0.01296495182**

Table 1 (b): Three regression models performed on the female dataset

3.1.3. Will changing the grip strength to categorical data (via thresholds) significantly improve the predictive power of our Random Forest model?

Classification:

- The performance of the three classification models performed on the male and female datasets is represented in Table 2.a and Table 2.b respectively.
- When observing the results from Table 2.a, we can see from the male classification table that the performance of all three models of classification was poor. This is because both accuracy and F1 scores are around 40 to 50 percent, an indicator of bad model predictive power. Considering this, the best performing model in Table 2 (a) is the logistic regression classification model, with slightly higher accuracy and f1 score compared to the other two models for the male dataset.
- Similar results can be seen in Table 2 (b). From the female classification table, it is clear that all models are poor predictors of the data. Considering this, logistic regression classification is also the best performing model compared to the other two models for the female dataset.

Model	Accuracy	F1 Score
Random Forest	0.4943820224719101	0.44021946375208876
Logistic Regression	0.5168539325842697	0.46079497402440495
Bagging	0.43820224719101125	0.44138463284530705

Table 2 (a): Accuracy and F1 score performance for the random forest, logistic regression, and bagging classifiers performed on the male dataset.

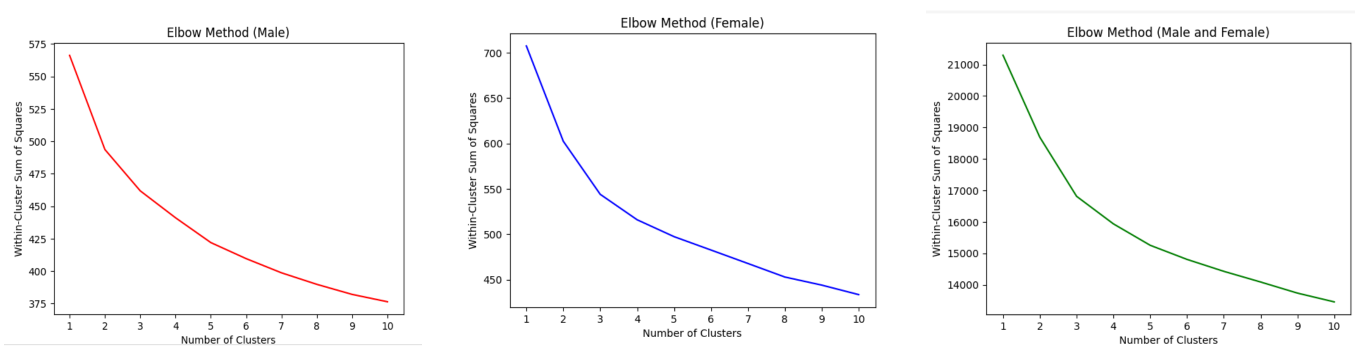
Model	Accuracy	F1 Score
Random Forest	0.43243243243243246	0.3582909832909833
Logistic Regression	0.5045045045045045	0.4286641091773409
Bagging	0.43243243243243246	0.43701375540998183

Table 2 (b): Accuracy and F1 score performance for the random forest, logistic regression, and bagging classifiers performed on the female dataset.

3.1.4. Are any of the emotional personality traits as measured by the HEXACO personality model, an accurate predictor of grip strength (and overall physical strength)?

Clustering:

- Plotting elbow plots for males only (**Figure 4. a**)), females only (**Figure 4. b**)), and both genders (**Figure 4. c**)).
- Plotting within-cluster sum of squares by the number of k-mean clusters (ranging from 1 to 10)
- When k= 4 clusters, the within-cluster sum of squares becomes much smaller.
- Four clusters are ideal for dividing the observations.



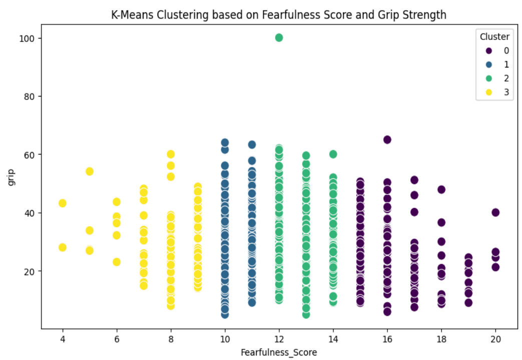
(a) (b) (c)

Figure 4. (**a**)Elbow Plot, Males only; (**b**) Elbow Plot, Females only; (**c**) Elbow Plot, both Males and Females.

Clustering (cont.):

- Ran K-means clustering for each personality trait (fearfulness, anxiety, dependency, and sentimentalism).
- Plotted the clusters vs their grip strengths.
- Printed the means of each group, and compared it to the mean of the entire dataset: 29.144002006018052.
- Done for each of the 4 listed traits, shown in **Figure 5**.

- The visualization of HEXACO personality scores in relation to grip strength represented across 4 clusters were graphically represented, as seen in **Figure 5**.

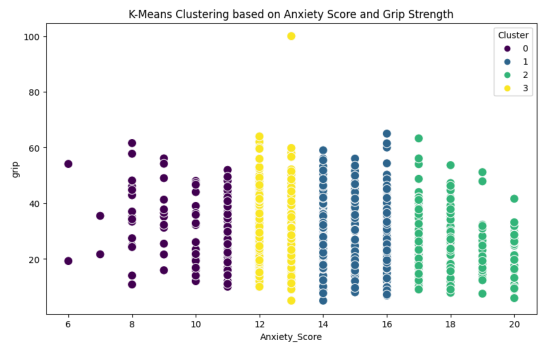


Mean Grip Strength for each Cluster (Fearfulness):

Yellow: 28.403740 Blue: 30.172509

Green: 30.265753 Purple: 25.603956

(a)

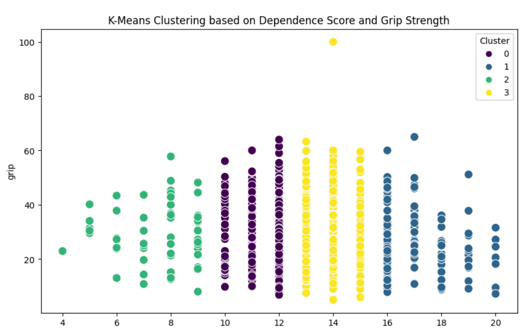


Mean Grip Strength for each Cluster (Anxiety):

Purple: 30.448281 Yellow: 29.482445

Blue: 29.848439 Green: 25.997558

(b)

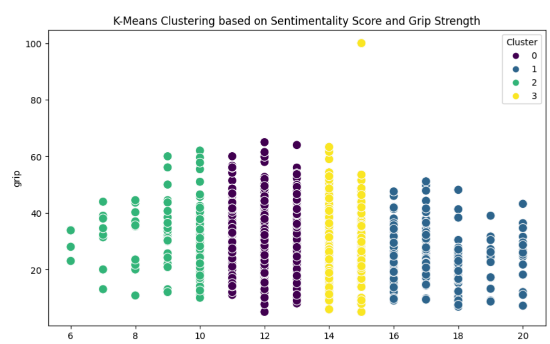


Mean Grip Strength for each Cluster (Dependency):

Green: 29.168730 Purple: 29.657360

Yellow: 29.689564 Blue: 26.416732

(c)



Mean Grip Strength for each Cluster (Sentimentality):

Green: 32.460476 Purple: 32.008391

Yellow: 27.975768 Blue: 24.390221

(d)

Figure 5. K-Means clustering plots based on given HEXACO scoring metrics. (**a**) Grip strength in relation to HEXACO personality score on fearfulness, (**b**) Grip

strength in relation to HEXACO personality score on anxiety, (**c**) Grip strength in relation to HEXACO personality score on dependence, (**d**) Grip strength in relation to HEXACO personality score on sentimentality

- As can be seen in **Figure 5**, there is a consistent decline in grip strength amongst the K-Means Clusters as we investigate the clustered groups with higher HEXACO scores. On the contrary, the grouped clusters with mid-level HEXACO scores result in having the highest grip strength on average compared to other groups. This is apparent across all 4 K-Means Clustering visualizations in **Figure 5** which represent the traits of fearfulness, anxiety, dependency, and sentimentality. With every personality trait in the combined (male & female) dataset, the highest scoring cluster has the lowest mean grip strength

- **Table 3** below summarizes the findings of clusters plotted against grip strength, as shown in **Figure 5.**

Trait	**Highest Mean Strength**	**Lowest Mean Strength**
Fearfulness	Mid Fearfulness	High Fearfulness
Anxiety	Low Anxiety	High Anxiety
Dependency	No Significant Group	High Dependency
Sentimentalism	Low Sentimentalism	High Sentimentalism

Table 3: Derived from **Figure 5**. Lists the trait being clustered on, the clusters with the highest mean grip strength, and the clusters with the lowest mean grip strength. Corresponds with Figure 5 parts a-d respectively.

- Using these results, we can conclude that the emotional personality traits as measured by the HEXACO personality model are in fact an accurate predictor of grip strength. Higher scores on these four dimensions of personality have – on average – lower grip strength compared to the average person in our dataset.

4. Discussion

In examining the relationship between HEXACO scores and grip strength through Figure 1, our findings consistently demonstrated a negative correlation. Specifically, higher scores in various HEXACO domains, such as anxiety or fearfulness, were consistently associated with lower grip strength. This suggests a potential link between psychological traits and physical capabilities, indicating that individuals scoring higher on certain HEXACO metrics might exhibit reduced grip strength.

Interestingly, our analysis revealed a positive correlation among different HEXACO scores. For instance, individuals with higher anxiety scores also tended to exhibit higher depression scores and other HEXACO traits. This interconnectedness among the HEXACO domains reinforces the idea of a broader psychological framework that encompasses multiple traits within an individual.

Our initial assumption that stressful conditions might prompt increased physical strength was challenged by the data. Instead, our findings suggest that the HEXACO model measures overall stress levels, not momentary stress responses. Therefore, it's more plausible to interpret these results as traits associated with reduced grip strength manifesting in individuals with higher scores in specific HEXACO domains.

This understanding provides a more nuanced perspective, indicating a potential relationship between psychological traits and physical abilities that warrants further exploration and consideration in future research.

While all our regression models prove to be very inaccurate, the best among them is the Lasso Regression. This can be possibly explained by the fact that Lasso prefers data with a small number of important features, with all other features having little to no importance. The two important features, Hex_29 and Hex_53, both question the subject about physical danger (Figure A1). This is interesting because all other questions revolve around emotional aspects, while these two more directly relate to physical action and activity.

The classification results indicate a subpar performance, suggesting that machine learning models struggle to accurately predict our target variable with the given data. This could be attributed to insufficient data to explain the target feature or a limited correlation between the predicting features and the target variable.

Another thing that can be seen from the table output is that compared to all three classification models, logistic regression classification performs the best in terms of both accuracy and F1 scores. There can be two possibilities for why this model performs better than. One is that the logistic classification model is generally simpler compared to the other two. Since our data is relatively "simple" with only twenty total features, it would make sense that this model performs better in predicting the data. The second reason is that the random forest and bagging classification models excel in capturing complex patterns in data. Since our dataset does not include any essential patterns, logistics regression classification would perform better compared to the other two models. Even though it's difficult to completely understand the complexity behind why some models perform better than others, these two considerations fit well in explaining the performance of our classification models.

Using k-means clustering to split each personality trait (fearfulness, anxiety, dependence, and sentimentality) into four clusters has provided us with some interesting results. We can see that from our visuals, high scores in all emotional fields indicated a lower-than-average mean strength (Table 3). Low grip strength indicates a person who easily gets scared and worried. Such an individual is very sentimental, reacting strongly to emotional feelings. In addition, the subject is very dependent on other factors to feel safe or calm. High grip strength can be observed in individuals with a medium fearfulness score, a low anxiety score, and a low sentimentality score. Dependence does not affect a high grip strength. We can conclude that this person is not prone to fear but not immune to its effects. The subject tends to not worry and makes careful decisions with factual consideration.

5. Conclusions

There is an overall positive correlation between HEXACO scores and other HEXACO scores. This was seen in Figure 1 (correlation heat map) and Figure 5 (k-means clustering plots). With that being said, there is a negative correlation uncovered between HEXACO personality scores in relation to grip strength.

The regression models all indicate a rather poor predictive power. We are unable to accurately predict grip strength based on the four personality traits. We can assume that the data itself needs more information added to it. Further psychological research must be conducted to add more features to the data for additional predictive power of grip strength.

The results of classification for this data provide insights into how this data can be improved for the future. Since all three classification models performed poorly, further development of that dataset is required for the models to be able to predict the data better. Specifically, more recordings of information will need to be added to the data including not only more patients to be examined but also to increase the number of features concerning strength. If more additional data on strength is included, then the models may be able to predict the target variable more effectively.

Our clustering model has given us much to consider. It can be seen from the results of Table 3 that a person who tends to get fearful, anxious, dependent, or sentimental easily will have a weak overall strength. We can infer that when a person is prone to worry or fear, they may not be confident in their strength of body or mind. In a "Fight or Flight" situation, those who are weak may tend to flee as opposed to strong individuals who may stand their ground. Our work can be further tied in with other methods for measuring strength in the future, allowing us to further predict a person's strength based on certain emotional traits. As our models stand right now, there needs to be further research done to improve their performances.

Author Contributions:

Conceptualization: Nicholas Nemkov and Elijah Campbell-Ihim;

Methodology: Anthony Simone and Andrew Nemkov;

Software: Claudia Iwinski and Elijah Campbell-Ihim;

Validation: Elijah Campbell-Ihim., Nicholas Nemkov, and Anthony Simone;

Formal analysis: Elijah Campbell-Ihim.;

Investigation: Elijah Campbell-Ihim and Claudia Iwinski;

Resources: Claudia Iwinski and Nicholas Nemkov;

Data Curation: Elijah Campbell-Ihim;

Writing—original draft preparation: Claudia Iwinski and Andrew Nemkov;

Writing—review and editing: Anthony Simone, Nicholas Nemkov, and Elijah Campbell-Ihim;

Visualization, Elijah Campbell-Ihim, Claudia Iwinski, Anthony Simone, and Nicholas Nemkov;

Supervision: Elijah Campbell-Ihim and Andrew Nemkov;

Project Administration: Elijah Campbell-Ihim and Anthony Simone;

All authors have read and agreed to the published version of the manuscript.

Data Availability Statement: The dataset implemented in this report is a union of three samples of data concatenated into a single data frame. The sample can be downloaded as CSV files under the names 'Sample_3.csv', 'Sample_4.csv', and 'Sample_5_corrected.csv' from kaggle.com under the link:

https://www.kaggle.com/datasets/thedevastator/physical-strength-correlation-with-fear-related?select=Sample_5_corrected.csv

Appendix A

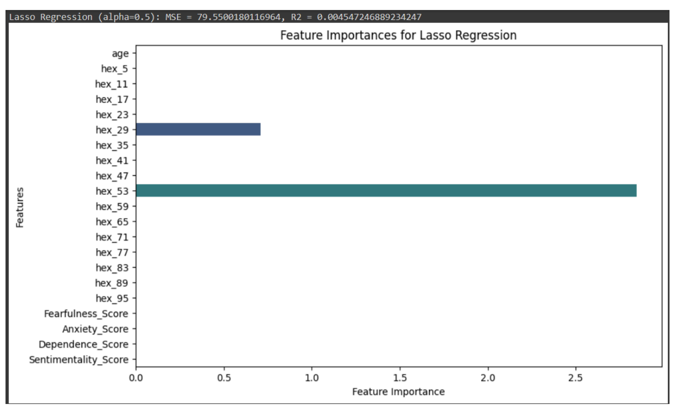


Figure A1: Feature Importances for Lasso Regression of the male dataset.

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