2024

Predict Mental Health Risks from Music Listening Patterns

Julie Campbell

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Business Problem

Your physical health can be affected by your mental health if neglected for too long. Music therapy has been invented to use the properties of music to help people improve their mental health. Some benefits include lower heart rate and blood pressure, relax muscle tension, release endorphins, relieve stress and encourage feelings of calm (Wong, 2023). This project will determine if music patterns can be used to predict users who experience severe symptoms from Anxiety, Depression, and/or OCD as base-line mental illnesses.

Background

The music and mental health survey results dataset was collected from Kaggle (Rasgaitis, 2023). It was posted to several different social media sites for participant responses. In the question set, mental illnesses were scaled from 0-10 according to the participant's view. It also collected information about frequency of music genre listened to such as hip hop, rock, lofi, etc. and other music listening habits. All responses were collected from September – November 2022.

Data Preparation

Analysis will focus on metrics that could be collected by a typical music application for future implementation. The following basic data preparation was completed: fill null with 0, alter dtypes to int, and code yes/no responses as 0/1. Severity of a mental illness can be categorized in multiple ways but the most utilized is the GAF scale from 0 to 100. The mental illness responses from 0 to 10 were then altered to fit that scale and then classified any response scored as 6 or higher was considered severe (Bhandari, 2023). A new feature was also created to count the number of genres that a participant rarely listened to at a minimum.

Methods

Since three mental illnesses will be measured as a response to patterns noticed with music listening, it will be considered a multi-label classification. Several classification models can be used to measure multi-label targets such as a classifier chain and multi-output classifier. Features will be selected based on the correlation to target values and the calculated p-value during the split of test/train.

Analysis

After data has been prepared, analysis was done on core features collected such as age and hours per day listening to music. You can find the results of the histogram of these features in Figure 1 and 2. Figure 1 shows that the respondents' age typically fell into 10-40 years old with most participants being 15-20 years old.

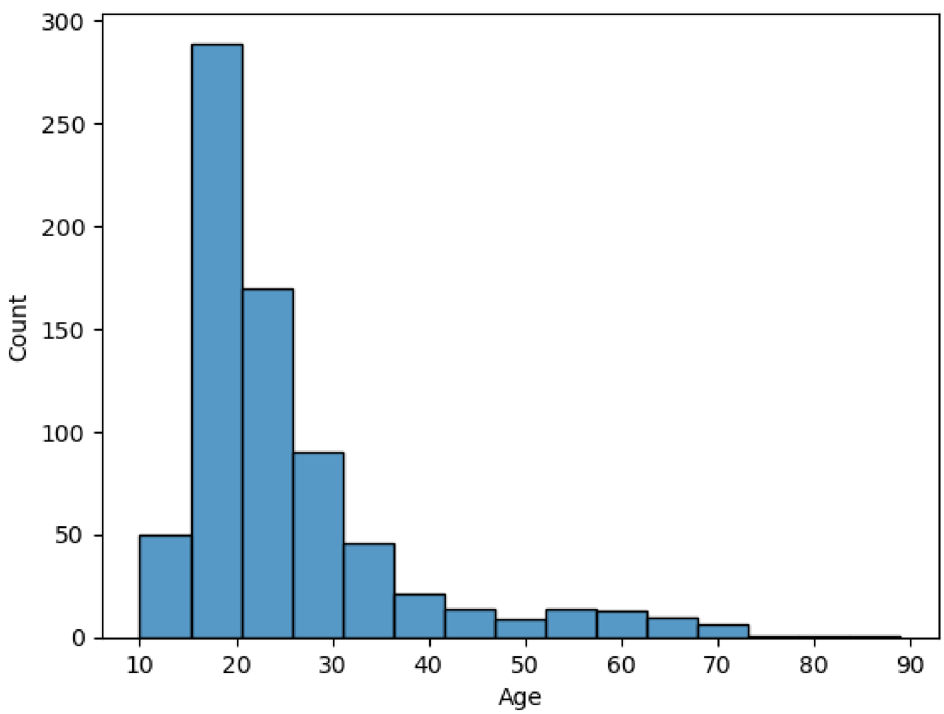


Figure 1: Age Histogram

A relationship was expected for listening to music at work and the number of hours listening to music based on the correlation between features. Most respondents stated that they listened to music less than 6 hours per day.

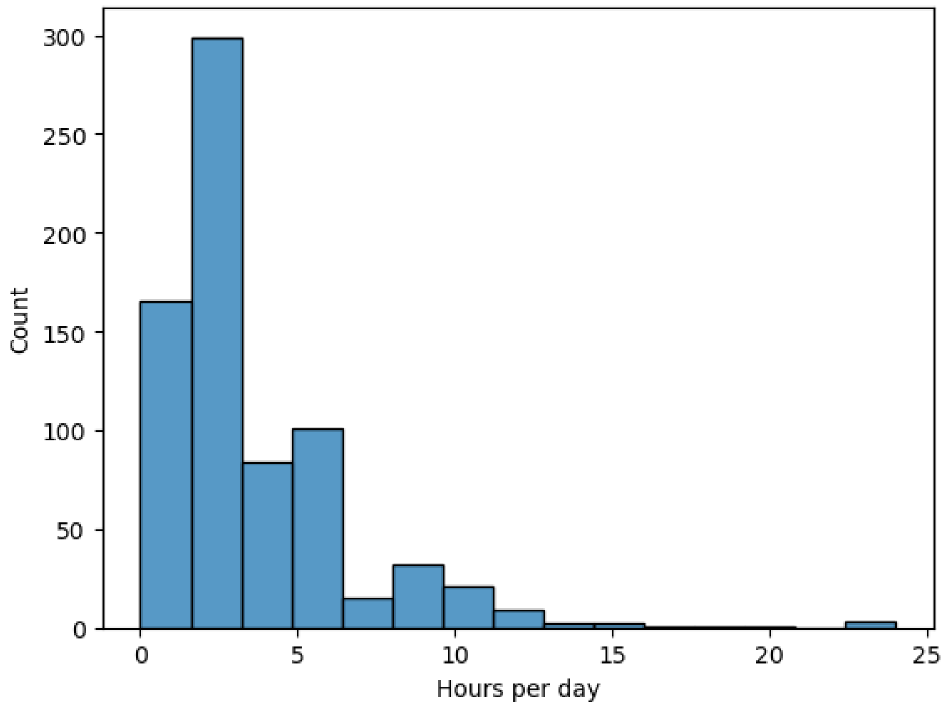


Figure 2: Hours per Day Listening to Music

Other patterns noticed were that rock, pop, and metal were rated as the top three favorite music genres and the number of music genres listened to typically ranged a count of 8 or more.

The correlation of features for anxiety, depression, and OCD seemed variant other than age, hours per day, the relationship between the three mental conditions, and the number of music genres listened to. Based on the p-values, the features in Table 1 were selected for model evaluation.

Feature Name	P-value
Age	0.0000000
Hours per day	0.0007078
Insomnia	0.0001288
Number of Genres	0.0293297

Table 1: P-value Evaluation

The data was split 60/40 due to the limited number of records collected during the survey collection. A standard scaler was applied through a pipeline when comparing model performance. The results of three different types of models were recorded in Table 2.

Types	Accuracy
Classifier Chain (Logistic Regression)	35.86%
Random Forest Classifier	31.87%
Multi Output Classifier (Logistic Regression)	30.28%

Table 2: Model Evaluation

Conclusion

The classifier chain of logistic regression models appeared to have the highest accuracy of the model types chosen for comparison. Based on the individual mental illness confusion matrixes, it appeared that the model's success was driven down by the accuracy of predicting OCD. Based on the correlation values with OCD and other features, this result was expected. Figure 3 - 5 show the associated confusion matrixes.

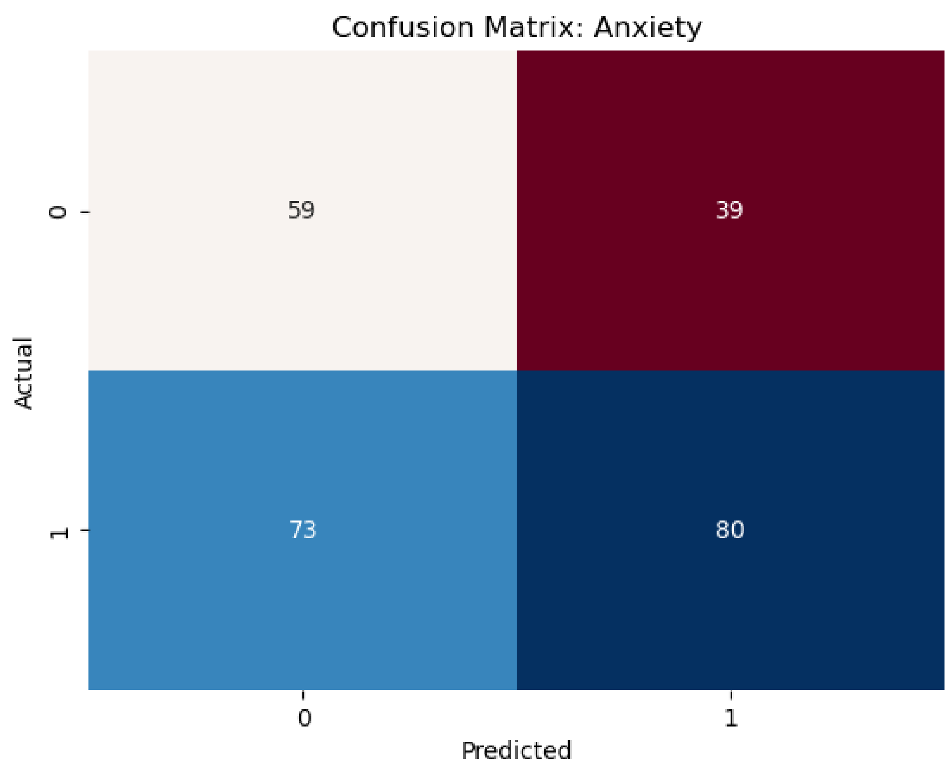


Figure 3: Anxiety Confusion Matrix

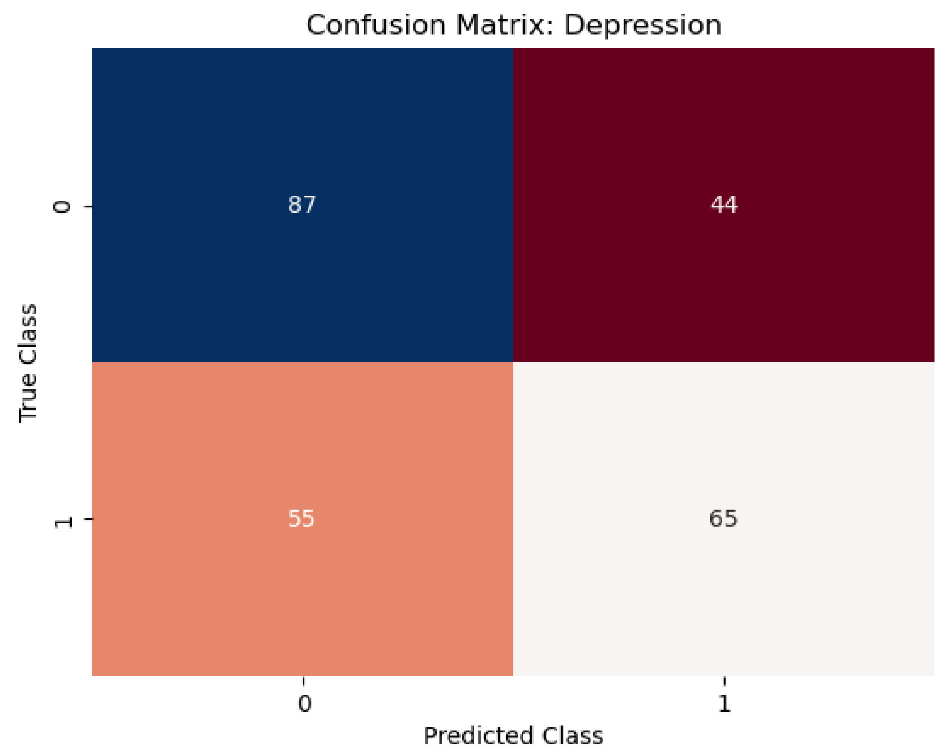


Figure 4: Depression Confusion Matrix

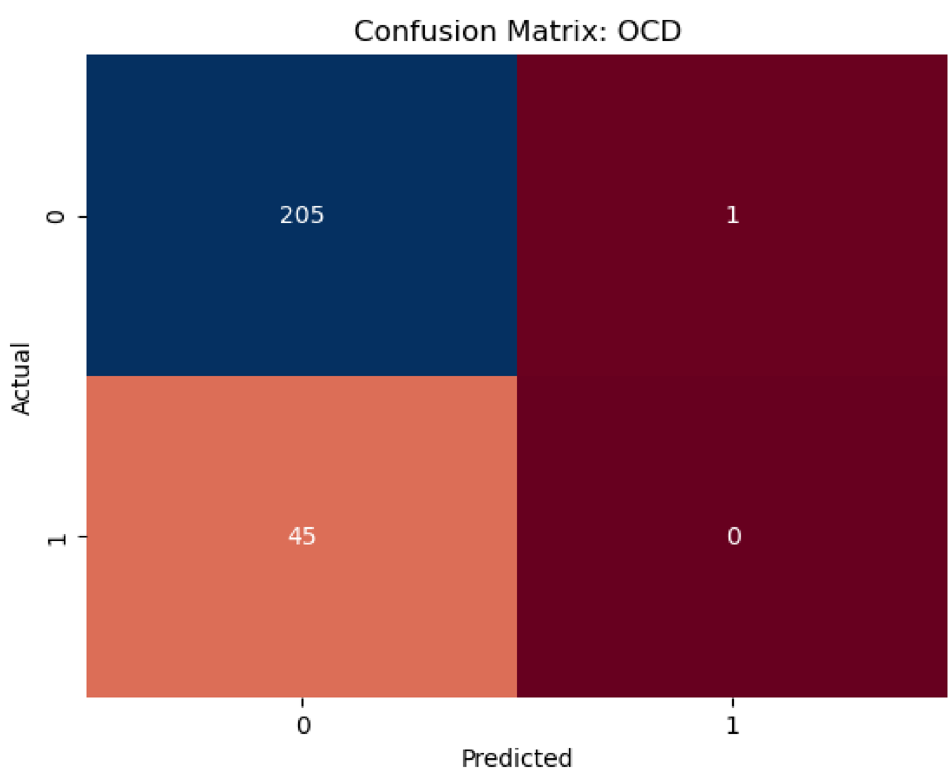


Figure 5: OCD Confusion Matrix

Assumptions

The first notable assumption made was that participants accurately accounted for their actual habits and not just their perceptions of how they respond. Next, it is assumed that participants understand the meaning of the 0-10 scale for anxiety, depression, insomnia, and OCD and shared a common definition of what their score reflects.

Limitations and Challenges

The main limitation of the model is the small representative sample used for analysis. It would be preferred to get actual music habits from applications such as Spotify or Amazon Music. Accuracy on a multi-label classification model was difficult as there were three closely related targets.

Future Applications

This research would have benefits to the community who studies psychology and mental illnesses to be able to display advertisements to a target audience for resources and services. Offerings would provide more awareness for society at large as well.

Recommendations

Due to the dataset size, I would recommend utilizing the same methodology on a larger dataset to determine if a better accuracy score could be collected. Although ~36% is not preferred, it does provide an initial step to future implementations.

Implementation Plan

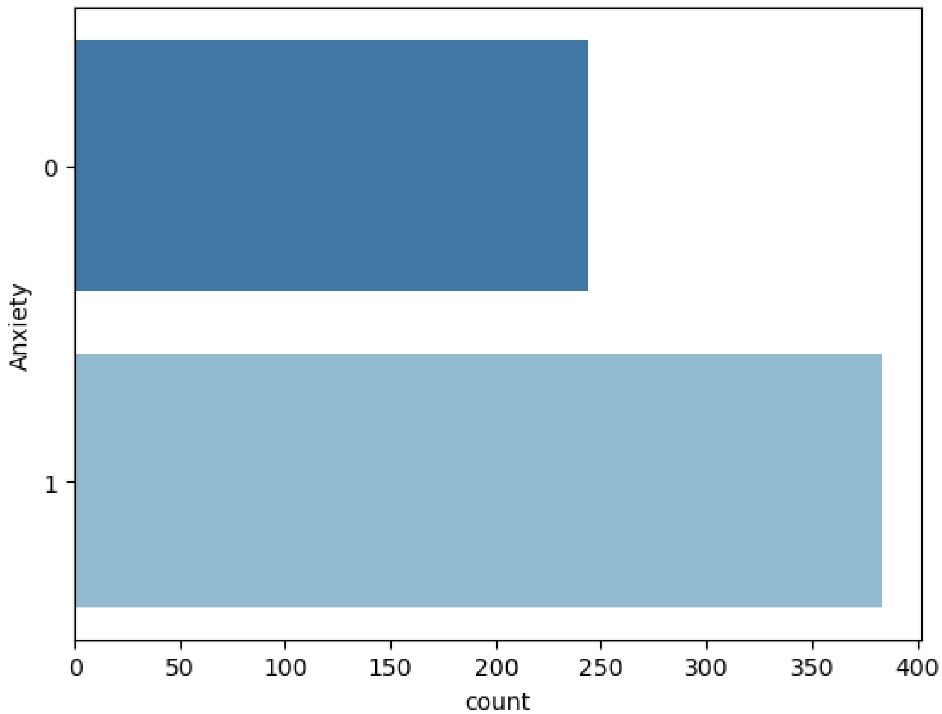
A corporate entity that has license and data about people's music listening and sleep habits could further research and provide targeted ads and information to local resources.

Ethical Assessment

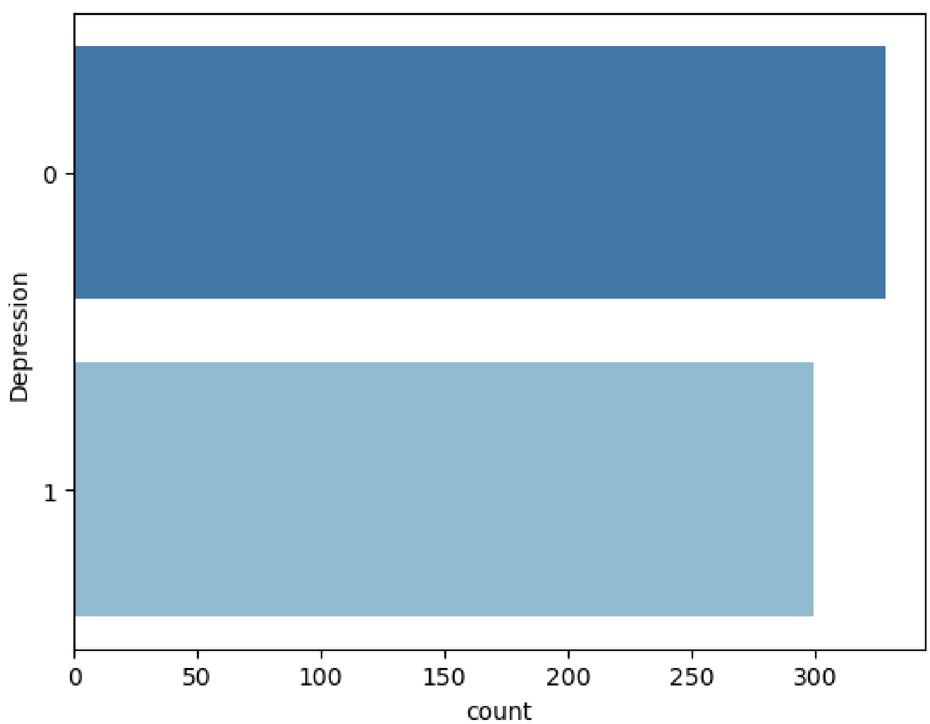
All participants consented to have their information recorded for educational purposes but may not consent to a larger study or licensed application of the data. Either consent from the individuals should be attained or a separate but similar dataset should be collected for modal implementation purposes.

Appendix

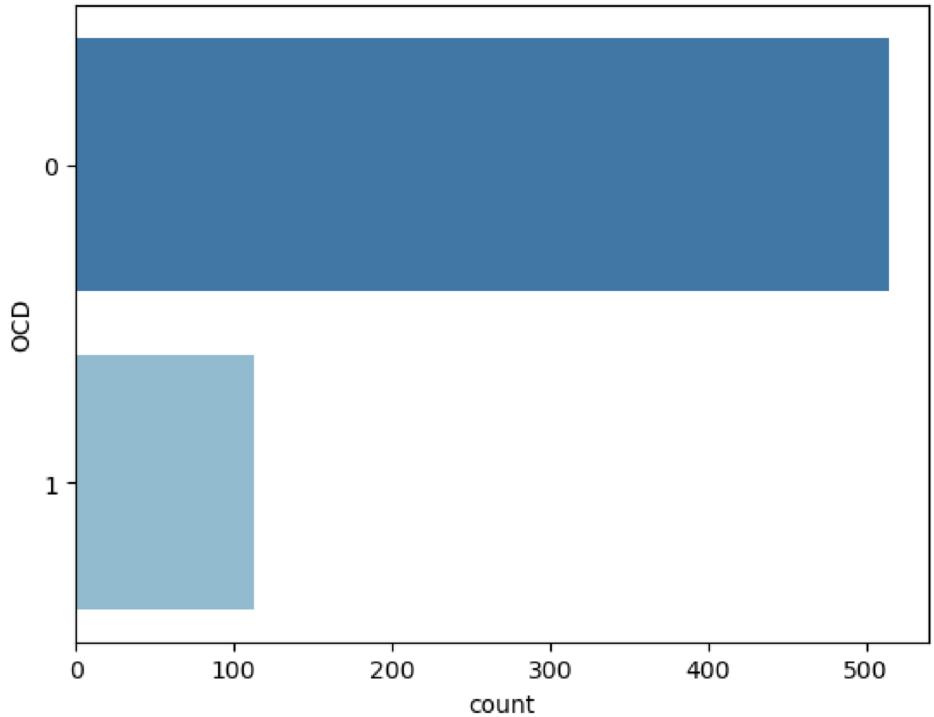
Appendix A: Mental Health Severity – Anxiety



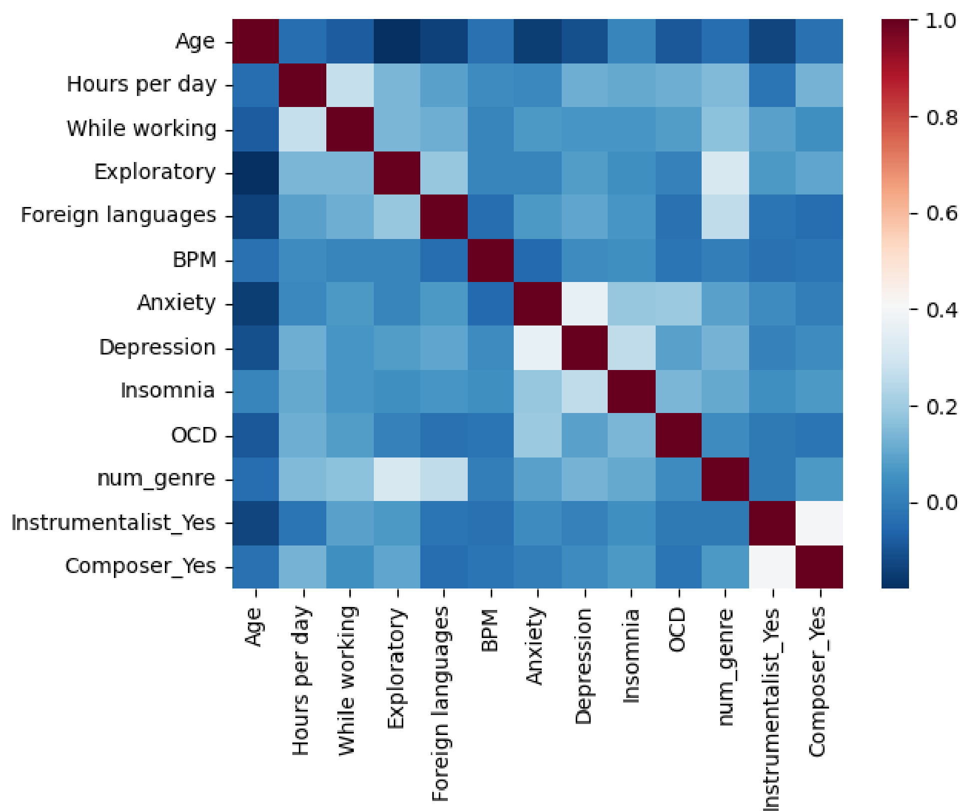
Appendix B: Mental Health Severity – Depression



Appendix C: Mental Health Severity – OCD



Appendix D: Correlation Matrix



References

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