Detecting Comorbidity Using Machine Learning

Yanessa Mari Lacsamana
Faculty of Science
University of Calgary
Calgary, Alberta
yanessamari.lacsaman@ucalgary.ca

Zain Sheikh
Faculty of Science
University of Calgary
Calgary, Alberta
zain.sheikh1@ucalgary.ca

Camilla Suarez Viltres
Faculty of Science
University of Calgary
Calgary, Alberta
camilla.suarezviltres@ucalgary. ca

***Abstract*—Comorbidity between mental disorders is a topic of great interest as professionals in the field have been recognizing emerging patterns between a variety of disorders. This research experimented with neural networks to find if machine learning could be as accurate as professional diagnoses and concluded with two neural network models that provided the highest accuracy for diagnosing comorbidity. The training data used was retrieved from "Psychiatric Comorbidity in Patients from the Addictive Disorders Assistance Units of Galicia: The COPSIAD Study," as it pertains to comorbidity and doing statistical calculations on its real-world data and visualising it for use as training data in the machine. The result concluded with the two models predicting certain relationships very well while others did not. More data will be needed to improve the accuracy of a professional diagnosis but the possibility of machine learning being used as a method of diagnosis may be possible in the future, as exhibited in this research.**

Keywords—comorbidity; machine learning; algorithm; mental illness;

I. INTRODUCTION

A. Comorbidity Definition

In contemporary society, mental health wellness is starting to become popular. Becoming more open to mental illnesses is less taboo and advocacy for mental health is everywhere these days but despite these positive developments, mental illness remains a significant source of disability for many individuals. It is also known that symptoms can be different for everyone with the same mental disorder and many could emerge with known symptoms existing and others not. This complicated web of intricacies when dealing with mental disorders provokes the need for further study on the topic. By exploring such studies, we allow for a better understanding of these disorders amongst patients and professionals alike.

Comorbidity as defined is “co-occurring or coexisting conditions” (Balingit). In this case, the presence of two or more mental disorders within an individual. In the largest population-based study of 2019 with nearly 6 million people and 83.9 million years worth of person data, it was found that diagnosis of a first mental disorder was associated with a 2-fold to 48-fold increased risk of diagnosis with a subsequent mental disorder with risks being the highest in the first year of the first diagnosis but persists even 15 years later (Gamse). Research such as this provides very important insights into the true complexity of mental illnesses.

B. Purpose Of The Research

The purpose of this research is to attempt to find if diagnosis of comorbidity using machine learning is just as effective as diagnosis through an actual person. One of the questions the research asks is: Given a set of certain symptoms and diagnosed disorders, is the result of a model from a machine-learned algorithm nearly as accurate as a professional diagnosis of another comorbid disorder? Professional diagnoses usually involve rigorous questions to ask the patient with. These professional diagnoses are usually done by therapists or sometimes, physicians. Although healthcare is free in Canada, many other countries do not have this case with therapist/physician diagnoses costing money that not many people can afford. This research, although not as reliable as a professional diagnosis, may help with shedding light on the possible comorbid illnesses that a person may not be aware of without the burden of the costs of a professional diagnosis.

II. LITERATURE OVERVIEW

A. Popular Traditional Methods of Research

Almost, if not all, research surrounding comorbidity usually involves time-tested methods such as interviews and questionnaires. A meta-analysis of PTSD comorbidity diseases in prison settings gathered studies involving clinical interviews, validated instruments leading to DSM or ICD diagnoses, or validated self-report questionnaires such as the PTSD checklist [3]. Another study involving ADHD comorbidity in Iranian children used structured psychiatric interviews assessing lifetime psychiatric disorders by DSM-IV criteria, using the Farsi version of the Schedule for Affective Disorders and Schizophrenia [4]. And lastly, A total of 3,585 (84.7 % of 4,231 births) children aged 6 years were assessed using the Development and Well-Being Assessment (DAWBA) from southern Brazil [5]. DAWBA is defined as “a novel package of questionnaires, interviews, and rating techniques designed to generate ICD-10 and DSM-IV psychiatric diagnoses on 5-16-year-olds” (Goodman, et al). In general, for performing interviews or questionnaires, popular criterias such as the DSM are used as a reference for the questions that were made.

B. Discussion

Deducing from these studies, interviews and questionnaires are the most common when it comes to research involving mental comorbidity. These interviews follow very specific criteria that create the questions themselves. Some advantage when using interviews and questionnaires is that the criteria used to make it are established methods, meaning that quality information would come out from following specific and well-known criteria. The second advantage is that interviews can provide detailed information about an individual's experiences and feelings, allowing a more nuanced understanding of their mental illness. This is especially important as people do not experience mental illnesses the same. The third advantage is flexibility because interviews can be tailored to an individual. The interviewer can also follow up with responses or clarification that can provide more meaningful data. Questionnaires in turn are cost-effective and can be administered to large populations. It is also objective due to its standardised nature. There also is anonymity with participants where they may feel more comfortable disclosing private information.

Interview and questionnaire methods also have their disadvantages. Constructing interview questions or self-report questionnaires may be time-consuming to conduct and analyse, especially if the sample size is large. There may also be bias in the resulting data as participants may be reluctant to discuss sensitive topics or admit to certain behaviours. This will skew the data and may not provide any good accurate information. For questionnaires, there is also limited information compared to interviews as questionnaires are usually limited to close-ended questions which may not provide any detailed information about an individual's experiences. There may also be bias in questionnaires where participants may not answer truthfully or may not take the questions seriously.

All in all, interviews and questionnaires are not perfect methods to gather data, but oftentimes most research around mental illness and comorbidity usually use these methods due to their advantages when it comes to nuance and the ability to gather the most personal experiences of an individual using simple questions.

III. DATA

The concept of using criteria such as the DSM, ICD, validated self-report questionnaires, DAWBA, etc. is similar to the concept of nodes in a neural network. Each node may represent a check in a checklist or criteria in the questionnaire that would go through stages, similar to layers in a neural network. The goal is to simulate these stages and criteria such that the result of a machine-learned algorithm is as or nearly as accurate as a professional diagnosis by a therapist or physician or at least as accurate as the aforementioned criteria that physical interviews and questionnaires follow.

A. Database

The dataset selected for exploration is "Psychiatric Comorbidity in Patients from the Addictive Disorders Assistance Units of Galicia: The COPSIAD Study," which captures the presence of various psychiatric disorders in patients receiving treatment for addictive disorders [6]. The dataset contains information for 2300 patients, with each row representing a patient and the columns indicating, in binary form, whether the patient tested positive for a specific disorder.

The columns are classified as general disorders and specific disorders. The general disorders consist of seven categories being Cognitive Disorder (Deldermamn), Schizo-psychiatric Disorder, Mood Disorder, Anxiety Disorder, Eating Disorder, Adjustment Disorder, Personality Disorder, and Impulse Control Disorder. The database also captures specific psychiatric disorders within each of these broader categories, such as specific types of mood disorders or personality disorders. For example, if a patient is identified as having a "manic disorder," the database will also indicate that the patient has a mood disorder. This level of detailed data has proven crucial in developing precise predictive machine learning models.

B. Dataset Statistics

A more general overview of the database was performed to get an understanding of surface-level comorbidities between the general categories of psychiatric disorders. The comorbidity between any two disorders was calculated as follows:

$$\frac{\left(count\left(disorderA\right) \cap count\left(disorderB\right)\right)}{count\left(disorderA\right) \cup count\left(disorderB\right)}$$

The subsequent table and heat map depict the results of the aforementioned calculations. From this general analysis, it became apparent that the comorbidity rates among the different mental health disorders were relatively low, with the highest rate being 11% between mood and anxiety disorders. Despite the low rates, there is still a certain level of comorbidity that warrants further exploration through more advanced machine learning protocols.

TABLE I. COMORBIDITY RATIOS

	Cognitive Disorder	Schizo-psychiatric Disorder	Mood Disorder	Anxiety Disorder	Eating Disorder	Adjustment Disorder	Personality Disorder	Impulse Control
Cognitive Disorder	1	0.0057	0	0	0	0	0.0021	0
Schizo-psychiatric Disorder	0.0057	1	0.0338	0.0221	0.0256	0.0048	0.0600	0.0250
Mood Disorder	0	0.0338	1	0.1120	0.0186	0.0073	0.0882	0.0466
Anxiety Disorder	0	0.0221	0.1120	1	0.0254	0.0109	0.0581	0.0638
Eating Disorder	0	0.0256	0.0186	0.0254	1	0	0.0141	0.0292
Adjustment Disorder	0	0.0048	0.0073	0.0109	0	1	0.0159	0.0133
Personality Disorder	0.0021	0.0600	0.0882	0.0581	0.0141	0.0159	1	0.0383
Impulse Control	0	0.0250	0.0466	0.0638	0.0292	0.0133	0.0383	1

Table II. Heat Map

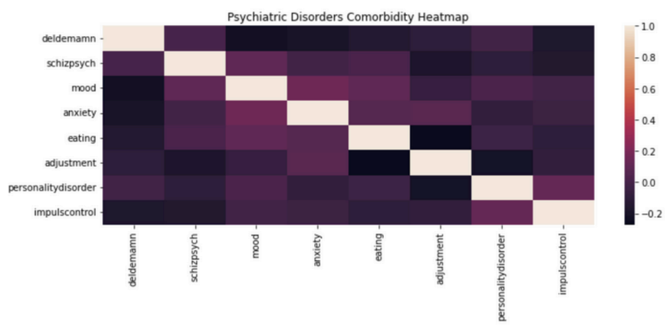

Table I contains the comorbidity ratios calculated to gain a quick overview of the general disorder category comorbidities with Table II visualising this finding. It is evident that comorbidity between two different general classifications is not the most common but still occurs in the dataset. It is also evident that individuals with mood, anxiety, impulse control, personality, and schizophrenic disorders have somewhat enough correlation for machine learning.

The totals for individuals diagnosed with each general category of mental disorders were also computed. However, for certain categories such as cognitive disorders (6/2300 entries), eating disorders (26/2300 entries), and adjustment disorders (39/2300 entries), the available data was insufficient for machine learning purposes. Therefore, a decision was made to exclude these specific illnesses as output from predicting comorbidity diagnosis using the machine.

C. Final Data For Machine Learning

To get a better idea of these comorbid relationships, here is the a second measure of comorbidity which will be used as data for the machine:

$$\frac{\left(count\left(disorderA\right) \cap count\left(disorderB\right)\right)}{count\left(disorderA\right)}$$

The criteria for choosing which two general categories to correlate with each other is if at least 5% of people with the 'primary' disorder has the indicated second mental disorder. The highest occurrence of comorbidity in the dataset was observed between anxiety disorders and mood disorders, with 28.7% of individuals diagnosed with anxiety disorders also having a diagnosed mood disorder. The following is the comorbidity ratios of each general categories:

- Schizophrenia and other psychotic disorders: 169 in total
  - Mood disorders = 23/169 = 13.6%
  - Anxiety disorders = 11/169 = 6.5%
  - Personality disorders = 38/169 = 22.5%
- Mood disorders: 511 in total
  - Personality disorders = 86/511 = 16.8%
  - Anxiety disorders = 94/511 = 18.4%
  - impulse control disorders = 29/511 = 5.7%
- Anxiety disorders: 328 in total
  - Personality disorders = 46/328 = 14.6%
  - Mood disorders = 94/328 = 28.7%
  - Impulse control disorder = 28/328 = 8.5%
- Personality disorders: 464 in total
  - Mood Disorders =86/464 = 18.5%
  - Anxiety Disorders = 46/464 = 9.9%
- Impulse control disorders: 111 in total
  - Personality disorders = 22/111 = 19.8%
  - Anxiety disorders = 28/111 = 25.2%
  - Mood disorders = 29/111 = 26.1%

IV. Machine Learning

To further investigate the comorbidity among psychiatric disorders, a machine learning model was developed to effectively predict whether a patient would test positive for a specific disorder, given data on their other specific disorders.

A. Input and Output Variables

For testing comorbidity within the database, challenges arose due to the size of the table. Obtaining the list of individuals with a diagnosed disorder for their primary condition resulted in a reduction of available data. Additionally, the ratio of those with a diagnosis versus those without in the smaller primary diagnosis table presented a concern for machine learning. To address these issues, a compromise was reached to group specific disorders into their general categories of disorders, specifically for the outputs. This approach provided a higher level of granularity, allowing for the development of more accurate machine learning models.

Using the previous data, the four general categories that would be used for outputs would be the predictions of anxiety disorder, personality disorder, impulse disorder, and mood disorder. Input 'primary' diagnoses for predicting comorbid anxiety disorder are schizophrenia and other psychotic disorders, mood disorders, personality disorders, and impulse disorders. Input 'primary' diagnoses for predicting comorbid personality disorder are schizophrenia and other psychotic disorders, mood disorders, anxiety disorders, personality disorders, and impulse disorders. Input 'primary' diagnoses for predicting comorbid mood disorder are schizophrenia and other psychotic disorders, anxiety disorders, personality disorders, and impulse control disorders. Input 'primary' diagnoses for predicting comorbid impulse control disorder are mood disorders and anxiety disorders.

B. The Models

To predict whether a patient would test positive for a specific disorder, a binary classification approach was used. Multiple hidden layers were created to achieve an accurate model for this classification problem. The initial layers included up to 50 nodes, which were gradually reduced to 1 node for the final layer with sigmoid activation code to provide the binary classification. The priority is accuracy of the diagnosis and since for the binary output, binary cross entropy was used as a base.

The first attempt involved the use of the reLu activation function. Which resulted in generally high accuracy. The problem of this activation function is the 'dying reLu problem'. It was not preferable for the machine to completely disregard certain input variables since people experience mental illness differently. So the research omitted this option of using reLu in general. The following is one of the first attempts with using reLu layers and 10 epochs.

```
tf.keras.layers.Dense(59, activation='relu'),
tf.keras.layers.Dropout(0.5),
tf.keras.layers.Dense(30, activation='relu'),
tf.keras.layers.Dropout(0.5),
tf.keras.layers.Dense(15, activation='relu'),
tf.keras.layers.Dropout(0.5),
tf.keras.layers.Dense(4, activation='relu'),
tf.keras.layers.Dropout(0.5),
tf.keras.layers.Dense(1, activation='sigmoid')
```

Fig.1. First attempt involving reLu activation functions

The accuracy achieved in the training and testing data for the models was as follows (train/test):

-Output: Personality Disorder:

Input: Schizo-psychiatric disorder: 91.6% / 92.5%

Input: Mood disorder: 80.3% / 86.0%

Input: Anxiety disorder: 90.0% / 90.3%

Input: Impulse Control disorder: 95.4% / 94.6%

-Output: Mood Disorder:

Input: Schizo-psychiatric disorder: 94.4% / 100.0%

Input: Personality Disorder: 81.9% / 88.3%

Input: Anxiety disorder: 81.6% / 81.6%

Input: Impulse Control disorder: 93.4% / 98.1%

-Output: Impulse Control Disorder:

Input: Mood Disorder: 73.9% / 73.9%

Input: Anxiety disorder:70.5% / 91.3%

- Output: Anxiety Disorder:

Input: Schizo-psychiatric disorder: 96.6% / 97.0%

Input: Personality Disorder: 87.4% / 80.3%

Input: Mood disorder: 71.4% / 71.2%

Input: Impulse Control disorder:91.6% / 90.9%

Furthermore, it was also found that increasing the number of epochs optimised the accuracy of the predictions greatly. As the following experiments increased epochs the results started to flatten at around 100. This, accompanied with the *adam* optimizer and a *binary cross entropy* loss function yielded best results.

The research also started to experiment with TanH activation and seLu functions. Which greatly affected accuracy.

```
tf.keras.layers.Dense(num_columns),
tf.keras.layers.Dropout(0.5),
tf.keras.layers.Dense(50, activation='tanh'),
tf.keras.layers.Dropout(0.5),
tf.keras.layers.Dense(50, activation='tanh'),
tf.keras.layers.Dropout(0.5),
tf.keras.layers.Dense(50, activation='tanh'),
tf.keras.layers.Dropout(0.5),
tf.keras.layers.Dense(50, activation='tanh'),
tf.keras.layers.Dropout(0.5),
tf.keras.layers.Dense(30, activation='tanh'),
tf.keras.layers.Dropout(0.5),
tf.keras.layers.Dense(15, activation='tanh'),
tf.keras.layers.Dropout(0.5),
tf.keras.layers.Dense(5, activation='tanh'),
tf.keras.layers.Dropout(0.5),
tf.keras.layers.Dense(1, activation='sigmoid')
```

Fig. 2. Attempt using TanH functions and more layers

The accuracy achieved in the training and testing data for the models was as follows (train/test):

- Output: Personality Disorder:

  Input: Schizo-psychiatric disorder = 77.0% / 79.4%

  Input: Mood disorder = 81.9% / 88.3%

  Input: Anxiety disorder = 87.4% / 80.3%

  Input: Impulse control disorder = 78.4% / 87.0%

- Output: Mood Disorder:

  Input: Impulse control disorder = 73.9% / 73.9%

  Input: Schizo-psychiatric disorder= 89.6% / 85.3%

  Input: Anxiety disorder = 71.4% / 71.2%

  Input: Personality disorder = 80.3% / 86.0%

- Output: Impulse Disorder:

  Input: Schizo-psychiatric disorder= 95.6% / 97.1%

  Input: Anxiety disorder = 91.6% / 90.9%

  Input: Mood disorder = 93.4% / 98.1%

  Input: Personality disorder = 95.4% / 94.6%

- Output: Anxiety Disorder:

  Input: Schizo-psychiatric disorder= 92.6% / 97.1%

  Input: Mood disorder = 84.1% / 81.6%

Input: Personality disorder = 90.6% / 90.3%

Input: Impulse control disorder = 70.5% / 91.3%

```
tf.keras.layers.Dense(num_columns),
tf.keras.layers.Dropout(0.5),
tf.keras.layers.Dense(50, activation='selu'),
tf.keras.layers.Dropout(0.5),
tf.keras.layers.Dense(50, activation='selu'),
tf.keras.layers.Dropout(0.5),
tf.keras.layers.Dense(50, activation='selu'),
tf.keras.layers.Dropout(0.5),
tf.keras.layers.Dense(50, activation='selu'),
tf.keras.layers.Dropout(0.5),
tf.keras.layers.Dense(1, activation='tanh')
```

Fig. 3. Another attempt involving tanh with the last layer's activation function being TanH

The accuracy achieved in the training and testing data for the models was as follows (train/test):

- Output: Personality Disorder:

  Input: Schizo-psychiatric disorder= 77.0% / 79.4%

  Input: Mood disorder = 81.9% / 88.3%

  Input: Anxiety disorder = 87.4% / 80.3%

  Input: Impulse control = 78.4% / 87.0%

- Output: Mood Disorder:

  Impulse control = 73.9% / 73.9%

  Input: Schizo-psychiatric disorder= 86.7% / 85.3%

  Input: Anxiety disorder = 71.4% / 71.2%

  Input: Personality disorder = 80.3% / 86.0%

- Output: Impulse Disorder:

  Input: Schizo-psychiatric disorder= 95.6% / 97.1%

  Input: Anxiety disorder = 91.6% / 90.9%

  Input: Mood disorder = 93.4% / 98.1%

  Input: Personality disorder = 95.4% / 94.6%

- Output: Anxiety Disorder:

  Input: Schizo-psychiatric disorder = 92.6% / 97.1%

  Input: Mood disorder = 81.6% / 81.6%

  Input: Personality disorder = 90.0% / 90.3%

  Input: Impulse control disorder = 70.5% / 91.3%

Since the TanH activation code is just a modified version of the sigmoid activation code – both to be used for binary classification – the research attempted to use TanH as the final layer, to see if it made any significant difference. The result was that the differences were very minute and that using TanH in the final layer did not help with the accuracy of the model.

D. Results

The experimentations with the neural networks concluded with two models that provided the highest accuracy for predicting the outputs. The following code snippets are coded in Keras and TensorFlow both using 100 with seLu being a big factor. This, accompanied with the *adam* optimizer and a *binary cross entropy* loss functions well.

```
tf.keras.layers.Dense(num_columns),
tf.keras.layers.Dropout(0.5),
tf.keras.layers.Dense(50, activation='selu'),
tf.keras.layers.Dropout(0.5),
tf.keras.layers.Dense(30, activation='selu'),
tf.keras.layers.Dropout(0.5),
tf.keras.layers.Dense(15, activation='tanh'),
tf.keras.layers.Dropout(0.5),
tf.keras.layers.Dense(4, activation='tanh'),
tf.keras.layers.Dropout(0.5),
tf.keras.layers.Dense(1, activation='sigmoid')
```

Fig. 4. First Model

```
tf.keras.layers.Dense(num_columns),
tf.keras.layers.Dropout(0.5),
tf.keras.layers.Dense(50, activation='selu'),
tf.keras.layers.Dropout(0.5),
tf.keras.layers.Dense(30, activation='selu'),
tf.keras.layers.Dropout(0.5),
tf.keras.layers.Dense(15, activation='selu'),
tf.keras.layers.Dropout(0.5),
tf.keras.layers.Dense(5, activation='selu'),
tf.keras.layers.Dropout(0.5),
tf.keras.layers.Dense(1, activation='sigmoid')
```

Fig. 5. Second Model

Results from the experiment concluded that predictions of a comorbid personality disorder and predictions of a comorbid impulse disorder were more efficient with the first model. Predictions of a comorbid mood disorder and predictions of a comorbid anxiety disorder yielded more accuracy with the second model.

The accuracy achieved in the training and testing data for the models was as follows (train/test):

-Output: Personality Disorder:

Input: Schizo-psychiatric disorder: 77.0% / 79.4%

Input: Mood disorder: 83.3% / 87.4%

Input: Anxiety disorder: 87.4% / 80.3%

Input: Impulse Control disorder: 78.4% / 87.0%

-Output: Mood Disorder:

Input: Schizo-psychiatric disorder: 73.9% / 73.9%

Input: Personality disorder: 91.1% / 85.3%

Input: Anxiety disorder: 91.1% / 85.3%

Input: Impulse Control disorder: 81.7% / 86.0%

-Output: Impulse Control Disorder:

Input: Mood Disorder: 93.6% / 98.1%

Input: Anxiety disorder: 91.6% / 90.9%

- Output: Anxiety Disorder:

Input: Schizo-psychiatric disorder: 96.3% / 100.0%

Input: Personality Disorder: 91.4% / 89.2%

Input: Mood disorder: 84.3% / 81.6%

Input: Impulse Control disorder: 70.5% / 91.3%

By utilising specific, granular disorders as predictors and implementing a multi-layered neural network, the models were able to somewhat accurately predict the presence of a particular disorder based on the presence of other disorders and others somewhat do not. Good accuracy in this research's metric would be 90% above since the diagnosis of illnesses must be very accurate. From this experiment, there are some relationships that the machine has not predicted quite well such as the relationship between any of the indicated disorders predicting impulse control disorders where accuracy for using the models only yielded low results with the highest only being 81.7% training accuracy. Mood disorder predicting personality, impulse control predicting mood, and mood predicting anxiety yielded accuracies in the low eighties, and anxiety disorder predicting personality disorder resulted in train accuracy in the high eighties.

V. Conclusion

This research aimed to answer the question: Given a set of certain symptoms and diagnosed disorders, is the result of a model from a machine-learned algorithm nearly as accurate as a professional diagnosis of another comorbid disorder?

Through this careful analysis of data on psychiatric disorders, provided the right data, machine learning can be used to create decently accurate predictions of the comorbidity of psychiatric disorders amongst patients. With accuracy rates of 96% in this experiment, the models proposed in this paper suggest that not only are there very real and prominent comorbidity patterns between disorders, but that individuals can use modern technology to make predictions of existing disorders, before the conclusion of a professional physician. This allows the potential for patients to look out for possible comorbid disorders they may have without the need for paying for a diagnosis. In places where healthcare is not free, such models can help guide patients toward discovering the patterns in their health. However, detailed information about specific disorders and symptoms must be taken into account in order to begin creating accurate predictive models.

This being said, the research was not able to create a model that yielded high accuracies for every single comorbid disorder. Some disorders simply did not share enough correlation with others or there was not enough data and thus found that some disorders were much harder to predict. With this variation in accuracy, the model was able to be extremely accurate for specific disorders and not as accurate for others. Therefore, depending on the disorder, there is indeed a machine learning model that can predict comorbidity within psychiatric patients, nearly as accurately as a professional diagnosis. However, the variation in accuracy from disorder to disorder ultimately limits the use of the machine learning model as a loose prediction, rather than a substitute for a professional diagnosis.

References

[1] Balingit, Angelica. "Comorbidity: Definition, Types, Risk Factors, Treatment & More." Healthline, 4 Apr. 2022, www.healthline.com/health/comorbidity#definition.

[2] Gamse, Caroline. "Mental Health Comorbidity: One Thing Leads to Another." Www.medpagetoday.com, 19 Feb ,2019, www.medpagetoday.com/resource-centers/mental-health-focus/mental-h \ealth-comorbidity-one-thing-leads-another/2408.

[3] Ghanizadeh, Ahmad, et al. "Comorbidity of Psychiatric Disorders and Parental Psychiatric Disorders in a Sample of Iranian Children With ADHD." Journal of Attention Disorders, vol. 12, no. 2, 2008, pp. 149–55, https://doi.org/10.1177/1087054708314601.

[4] Petresco, Sandra, et al. "Prevalence and Comorbidity of Psychiatric Disorders among 6-Year-Old Children: 2004 Pelotas Birth Cohort - Social Psychiatry and Psychiatric Epidemiology." SpringerLink, Springer Berlin Heidelberg, 1 Feb. 2014, https://link.springer.com/article/10.1007/s00127-014-0826-z.

[5] Goodman, R, et al."The Development and Well-Being Assessment: Description and Initial Validation of an Integrated Assessment of Child and Adolescent Psychopathology." PubMed, 1 July 2000, pubmed.ncbi.nlm.nih.gov/10946756.

[6] Pereiro, César, et al. "Psychiatric Comorbidity in Patients from the Addictive Disorders Assistance Units of Galicia: The COPSIAD Study." PLOS ONE, Public Library of Science, 18 June 2013, https://journals.plos.org/plosone/article?id=10.1371%2Fjournal.pon e.0066451.