Utilizing Pattern Mining and Classification Algorithms to Identify Risk for Anxiety and Depression in the LGBTQ+ Community During the COVID-19 Pandemic

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ABSTRACT

In this paper, we examine the results of pattern mining and decision trees applied to a dataset of survey responses about life for individuals in the LGBTQ+ community during COVID, which have the potential to be used as a tool to identify those at risk for anxiety and depression. The world was immensely affected by the pandemic in 2020 through 2022, and our study attempts to use the data from this period to analyze the impact on anxiety and depression. First, we used the FP-growth algorithm for frequent pattern mining, which finds groups of items that frequently occur together, and utilized the resulting patterns and measures to determine which features were significant when inspecting anxiety and depression. Then, we trained a decision tree with the selected features to classify if a person has anxiety or depression. The resulting decision trees can be used to identify individuals at risk for these conditions. From our results, we also identified specific risk factors that helped predict whether an individual was likely to experience anxiety and/or depression, such as satisfaction with their sex life, cutting meals, and worries of healthcare discrimination due to their gender identity or sexual orientation.

CCS CONCEPTS

• **Applied computing** → *Psychology*; • **Computing methodologies** → **Machine learning algorithms**; **Rule learning**; **Classification and regression trees**.

KEYWORDS

datasets, COVID-19, COVID, LGBTQ+, classification, decision tree, pattern mining, association rules, anxiety, depression, mental health, FP-growth

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1 INTRODUCTION

The COVID-19 pandemic changed lives around the world with new public health measures, financial losses, and contradictory news [23]. The effects of COVID-19 on mental health and well-being around the world have been studied in several ways. The psychosocial effects of pandemics have been researched, finding that the trauma from a life-threatening pandemic may cause depression and anxiety disorders to develop [23]. Attempts to prevent these disorders from developing are recommended to prioritize those who are more at risk for these disorders, although it may be difficult to identify them, especially in the midst of a public health crisis such as a pandemic.

In this paper, we use frequent pattern mining and a decision tree classification algorithm, which have the potential to be used as a tool to identify those at risk for mental health concerns including anxiety and depression. Our goal is to take demographic and lifestyle factors and utilize this information to predict people at risk for anxiety and depression. We focus on individuals in the LGBTQ+ community, as they were the demographic of the survey used to collect our data. This survey was administered through the gay social network, Hornet.

First, we used the FP-growth algorithm, which finds groups of items that frequently occur together, on a dataset of survey responses about life during COVID. The survey included demographic and lifestyle factors, effects of COVID, and measures of mental health. We used the patterns resulting from FP-growth, and measures of the quality of these patterns, to determine which features were significant when considering anxiety and depression. Then, we attempted to train a decision tree algorithm to make trees that classify if a person has anxiety or depression. The resulting decision trees are intended to identify a person at risk for these conditions, rather than providing a diagnosis.

When used on COVID-19 data, these algorithms provide an opportunity to identify people at risk for mental health concerns during a pandemic with certainty that these findings have statistically significant evidence behind them. We also found several connections between specific demographic, mental health, and lifestyle factors with anxiety and depression. For predicting anxiety, the most notable factors were cutting meals, worries of healthcare discrimination due to sexual orientation or gender identity, and satisfaction of their sex life. For predicting depression, the most notable factors were cutting meals, worries of healthcare discrimination due to sexual orientation or gender identity, satisfaction of their sex life, and age.

Our research makes the following contributions: 1) analyzes unique data to provide insight on how COVID-19 indirectly affected anxiety and depression in individuals in the LGBTQ+ community. 2) Constructs decision trees to identify those at risk for anxiety and depression using data specific to the COVID-19 pandemic. 3) Provides a tool to identify individuals in the LGBTQ+ community at risk for anxiety and depression during a similar crisis. 4) Identifies specific risk factors for anxiety and depression in individuals in the LGBTQ+ community during the COVID crisis.

2 DEFINITIONS

2.1 Pattern Mining and FP-growth

Frequent pattern mining is the process of identifying items that frequently occur together in a dataset. It is useful for finding relationships such as associations and correlations in data [13]. Pattern mining is related to association learning, which is a rule-based machine learning method that finds relationships between variables with a focus on correlations originally proposed by Agrawal et al [1]. Most statistical tests can only determine if one item has a high likelihood of occurring with another item. However, pattern mining can find several items in a group simultaneously that tend to occur together.

FP-growth is a frequent pattern mining algorithm that arranges items in descending order by frequency to make a tree that recursively mines for significant patterns. [14] The tree is built using the list of frequent items to compress the database into a tree with the association information. The mining starts with all of the single-length patterns, the items that frequently occur by themselves, and finds all of the frequent patterns containing two items with the single-length patterns at the end. These frequent patterns create another tree, and then the mining occurs again recursively until it reaches the maximal length patterns [13].

From the resulting set of frequent patterns, we can produce association rules, which use the presence of some items (the antecedents) to predict the presence of other items (the consequents). Measures for the quality of association rules include support, confidence, and lift. Support is a measure of how often the underlying pattern occurs in the dataset. To be considered "frequent", the support for a pattern must be above a chosen threshold. Confidence is a measure indicating how often the association rule is true by dividing the number of times the pattern occurs by the number of times the antecedent is present without the consequent. Lastly, lift measures how often the antecedent and consequent in an association rule occur together compared to what we would expect if they were statistically independent.

2.2 Classification and Decision Trees

A classification model uses features to predict a categorical target variable. A decision tree classifier predicts the target variable with simple decision rules on the features. Machine learning can be used to construct a decision tree from labeled data. These algorithms use various metrics to determine the "best" feature to split on at each node of the tree. One such metric is Gini impurity, which we will use. Decision trees have the advantage of being highly interpretable since each decision node is a binary condition on a single feature.

3 BACKGROUND

3.1 COVID-19

In 2019, a coronavirus SARS-CoV-2 outbreak began in Hubei Province of the People's Republic of China and spread to other countries, becoming a global health emergency in early 2020. COVID-19 originated from SARS-CoV-2 transitioning and spreading from animals to humans at a seafood market in Wuhan, China [30]. The pandemic, known by the public as COVID-19, has continued into 2021 and 2022. During this time, people have faced unfamiliar public health measures that infringe on personal freedoms, reduction or loss of income and conflicting messages and news from authorities [23]. People were confined to their homes amidst new experiences of stay-at-home orders, quarantine, and isolation.

Lockdowns were put in place in many countries to prevent the spread of COVID-19, lasting approximately 35 days on average [4]. In some countries such as South Africa, only essential businesses remained open, and soldiers and police patrolled the streets to enforce the lockdown [16]. Many people stayed confined in their homes throughout most of 2020 and early 2021 before the vaccines were widely available to the public. Many workplaces and schools closed or moved online, and social gatherings were greatly discouraged. Research in disaster mental health has found that emotional distress is widespread among those affected, and COVID-19 was no different [23]. In a study of quarantine experiences and attitudes in China, more than 58% of those surveyed reported anxiety, 35% reported panic, and 16.6% reported helplessness [22].

3.2 Anxiety, Depression, and Dating During COVID

There are already several studies on people at risk for anxiety and depression. Women, unmarried people, and unemployed people are more likely to have current symptoms of depression [27]. In addition, cardiovascular disease, diabetes, asthma, smoking, physical inactivity, obesity, and heavy drinking are associated with lifetime diagnoses of anxiety and depression [27]. There has been substantial research on COVID-19 and its impact on anxiety and depression. Common coping mechanisms for stress due to COVID-19 included self-distraction, denial, substance use, behavioral disengagement, venting, planning, religion, and self-blame, and people with more stress engaged in these behaviors at a higher level [29]. The incidence of anxiety and depression was twice as common for individuals quarantining in an affected area compared to individuals quarantining in unaffected areas. They also concluded that community screening during an epidemic might reduce the risk of depression and anxiety [28].

Online dating has already been popular due to access and communication to a multitude of potential romantic partners. During the COVID-19 lockdown, all relationships, including romantic and sexual relationships, moved online as people were confined to their homes. Due to so much time alone, as well as some losing their jobs to the pandemic, single people spent more time using dating apps [8]. However, online dating also became a game or tactic to ease boredom, and also brought up issues of fully being able to trust the people that they were talking to [12]. Maintaining relationships instead of nding them during COVID-19 was di cult and stressful. People missed not being able to see their partners, di culty communicating, and a lack of external stimuli[12].

3.3 Hornet

Hornet is a gay social network with over 25 million users worldwide founded in 2011 by Christof Wittig, to inspire and empower gay men to create a global, connected community that moves society forward. It is the top gay dating app in several countries, including Brazil, France, Russia, Taiwan, and Turkey, and is rapidly gaining users in the United States. On average, users spend over 100 minutes a week in the app and collectively sent 21 million messages a day using Hornet. Like many social media apps, the Hornet app contains a feed with a user's followed and nearby accounts and allows users to post short videos and messages.

4 RELATED WORKS

4.1 Pattern Mining

Several papers have been published on pattern mining algorithms and techniques [13][11][31]. Pattern mining was originally proposed in 1993 by Agrawal et al [1]. Since then, several pattern mining techniques have been developed, including Apriori and FP-growth. Apriori is a downward closure property among frequent itemsets where each sub-itemset is frequent, observed by Agrawal and Srikant in 1994 [2]. However, Apriori su ers from generating a large number of candidate sets and checks the candidates by repetitively scanning the database and checking with pattern matching. FP-growth, a method developed by Han et al, uses pattern fragment growth instead of candidate generation to mine all frequent itemsets [15].

4.2 Pattern Mining and Classi cation For Diseases

Pattern mining has been used to diagnose and identify risks for mental and physical diseases [32][7][5]. Zhang, Long, and Ott developed a pattern mining strategy called AprioriGWAS, which used the Apriori algorithm and conditional permutations to control effects of singular variants when testing the e ects of gene variations [33]. Their pattern mining technique found 97% of the signi cant patterns found by exhaustive search and outperformed three classical genetic models for detecting genes. Chaves et al used association pattern mining to discover patterns in activated brain areas to try to diagnose early Alzheimer's disease [6]. Using image classi cation dependent on the patterns they found, their model had 94.87% accuracy and outperformed other recent computer-assisted methods for diagnosing Alzheimer's disease.

Classi cation has also been used to diagnose and identify risks for diseases [17][10][20][24]. Salhi, Tari, and Kechadi used neural networks and support vector machines on heart health data to classify those with heart disease [25]. They had 93% accuracy in classifying between healthy and sick patients and found that neural networks performed best on their dataset. Koutsouleris et al used support vector machines to classify magnetic resonance images of healthy and at-risk mental state (ARMS) participants [18]. They had approximately 81% accuracy classifying healthy and ARMS participants solely using structural neuroanatomical images.

4.3 Tools for Risk of Mental Illness During COVID

There have been several screening tools developed for mental illness in response to COVID [3]. Chung et al. created the Stress and Anxiety to Viral Epidemics-9 (SAVE-9) scale to examine the e ects of COVID-19 on the stress and anxiety of healthcare workers with a two-factor structure for anxiety and work-related stress [9]. They determined that their scale had similar reliability and validity of similar assessments, and screened 22.8% of participants with anxiety that did not have a high enough score for identifying anxiety with GAD-7, a common assessment for Generalized Anxiety Disorder. Lee developed the Coronavirus Anxiety Scale (CAS), which screens for possible anxiety, although the questionnaire focuses on anxiety and trauma-related reactions [21]. The questionnaire contained questions to assess social attitudes, psychological e ects, maladaptive coping, and functional impairment. Con rmatory factor analyses found that except for race, the scale measured anxiety similarly across di erent demographic groups, but was determined to still be valid for all groups.

4.4 Previous Work with the Dataset

The dataset that we used to train our models was previously used to investigate HIV treatments and care impacts of COVID-19 among gay men and and other men who have sex with men [26]. Santos et al found that gay men and MSM experienced consequences to their nances, mental health, and HIV testing and treatment. They concluded that the rates of anxiety and depression did not di er by HIV status, however, those who lost their jobs during the pandemic had higher rates of these mental health concerns. Of those who lost their jobs, 27.6% reported feeling depressed nearly every day in the prior two weeks, compared to 11.4% of those who did not lose their jobs. They recommended that better strategies to maintain health and well-being should be developed to address the unique needs of sub-populations of gay men and MSM, including immigrants, the uninsured, and racial and ethnic minorities.

5 EXPERIMENT SETUP

5.1 The Data

Our dataset was collected by a COVID-19 Disparities survey administered by Hornet. Hornet wanted to understand how Coronavirus was impacting their users and conducted a survey using their app. Data was collected between April 16, 2020, and May 4, 2020, through an invitation to participate in a brief 58 question survey that included questions about their demographics, mental health, and the impacts of COVID-19 on their nancial, emotional, and physical wellbeing [26]. All 13031 participants were over 18 and provided informed consent, and due to the purpose of the app, a large majority of participants were male. 6814 (52.29%) participants had anxiety, 3797 (29.14%) did not have anxiety, and 2420 (18.57%) did not answer the question. In contrast, 4408 (33.83%) participants had depression, 6342 (48.67%) participants did not have depression, and 2281 (17.50%) participants did not answer the question.

To prepare and clean the data, we dropped repetitive and poorly framed questions (ex: Since the COVID-19 crisis began, have you been staying in?) to eliminate some noise. In order to prepare the data for frequent pattern mining, we bucketed values of variables to convert them to categorical variables with a small number of values. Data was bucketed to make continuous variables such as age into categories. Variables on a 5 point scale, such as on a scale of none, somewhat, moderately, very, and extremely were bucketed to 3 categories of low, medium and high. Questions with yes and no responses that had a measures of severity (slightly or extremely) were bucketed into either yes or no. Additionally, we converted each record to a list of its values. These values served as the items for frequent pattern mining. For example, for a frequent pattern with being physically safe and not cutting meals frequently occurring with no anxiety, being physically safe and not cutting meals are the items in that pattern.

To determine if someone had anxiety or depression, the PHQ-4 questionnaire was asked by the survey[19]. These questionnaire rates nervousness, worrying, hopelessness, and little interest in doing things on a scale from 0-3. These numbers are determined by how frequently these issues were experienced in the past 2 weeks, where 0 is not at all, 1 is several days, 2 is more than half of the days, and 3 is nearly every day for each problem. When adding scores together, a score greater than or equal to 3 for nervousness and worrying suggests anxiety, and a score greater than or equal to 3 for hopelessness and little interest in doing things suggests depression.

5.2 FP-growth and Decision Trees

We used the FP-growth algorithm from PySpark and the decision tree classi er from Scikit-Learn. Due to a large amount of data and time to run FP-growth, we only generated frequent patterns with 8 or fewer items. We focused on results with anxiety and depression, so the decision tree classi er only used features contained in patterns with anxiety as a consequent for the anxiety model, and did the same with depression for our depression model.

6 RESULTS AND ANALYSIS

6.1 FP-growth

When training the FP-growth algorithm on our data, we experimented with changing the minimum support, minimum con dence, and the number of partitions, which determines the maximum number of antecedents in a pattern. We found that 3 or 4 antecedents were enough to yield most, if not all, signi cant association rules. We also found that after support gets very low (around .08), most patterns have several antecedents that were frequent in the data and hence have low lift, which indicated that the patterns are statistically insigni cant. For nding signi cant patterns in the data, we disregarded all patterns with a lift less than 1.2 and support less than .077, thresholds that were chosen experimentally.

6.1.1 Anxiety. Table 1 shows some of the association rules mined with either anxiety or no anxiety as a consequent. These association rules indicate that the patterns from FP-growth align with what we would expect as possible conditions that would accompany an anxiety diagnosis. The lift is greater than 1 for every association rule, which shows that the variables occur together more frequently than they would if they were statistically independent. Therefore, we believe that the FP-Growth association rules may identify someone at risk of anxiety.

Antecedent	Anxiety	Conf	Lift	Sup
Lonely since COVID	Yes	0.37	1.88	0.13
Low depressed	No	0.88	1.69	0.33
High happiness	No	0.75	1.43	0.21
Little suicidal ideation	No	0.65	1.24	0.19
Not lonely since COVID	No	0.75	1.43	0.16

Table 1: Anxiety Patterns Anticipated By Diagnosis

Table 2 contains a subset of association rules with anxiety as a consequent. The third and fourth antecedents are usually the same variables across all association rules, such as homosexuality being legal in their country of residence, drug use, and sex work. All association rules have a lift greater than 1, showing that the variables occur together more frequently than they would if they were statistically independent. Like in Table 1, association rules with anxiety tend to have a con dence around 30%, whereas association rules without anxiety have con dence around 70%.

Table 4 contains the association patterns with the most lift. These patterns are the most likely to occur together as opposed to statistically independent out of all of the anxiety association patterns. All of top lift patterns had Anxiety" as a consequent. The association pattern with the most lift shows that being gay and single have a strong relationship with anxiety. The con dence shows that 30% of people who were gay and single also had anxiety. The lift shows that someone having anxiety given that they are gay and single is 1.55x more likely than if it was statistically independent. The support shows that 8.17% of people in our dataset were gay, single, and anxious. Note that since this data was collected from a gay social apps used for purposes such as dating, and a majority of the people in our dataset had anxiety, this association pattern may be speci c to this dataset and may not generalize well to a larger population.

6.1.2 Depression. Similar to Table 1, FP-growth identi ed association rules with depression as a consequent consistent with a depression diagnosis. High happiness and low anxiety, little interest, and worrying were all antecedents for low depression, whereas high worrying was an antecedent for high depression. This indicates that the patterns from FP-growth align with what we would expect as possible conditions that would accompany a depression diagnosis. Therefore, we believe that the association rules resulting from FP-growth may be useful for identifying someone at risk of depression.

Table 3 contains the association patterns with the most lift for depression. There were no association rules with depression as a consequent. To save space on the graph, Movement somewhat restricted" was shortened to Movement restricted". Similar to Table 2, the fourth and fth antecedents are usually the same variables across all association rules such as homosexuality being legal in their country of residence, sex work, and having access to masks. All association rules have a lift greater than 1, showing that the variables occur together more frequently than they would if they were statistically independent. Association rules with no depression as a consequent tended to have con dence around 60-80%, and there were no association rules with depression as a consequent that met our thresholds.

Similar to Table 4, all of the top lift patterns had no depression as a consequent. The top lift association pattern shows that being emotionally safe, not losing health insurance, HIV negative, and homosexuality being legal in their country have a strong relationship with no depression. The con dence demonstrates that 82% of people who are emotionally safe, not losing health insurance, HIV negative, and homosexuality being legal in their country also did not have depression. The lift of this pattern shows that someone not having depression given that they are emotionally safe, not losing health insurance, HIV negative, and homosexuality being legal in their country is 2.2x more likely than if it was statistically independent. The support shows that 8.2% of people in our dataset being emotionally safe, not losing health insurance, HIV negative, and homosexuality being legal in their country, and are not depressed.

6.2 Decision Trees

A portion of the dataset had missing values for our target variables, and we dropped records with those missing values. We were able to use 72.8% of the data for predicting anxiety and 79.3% of the data for predicting depression. We chose to focus on decision trees since they could easily be used by a practitioner working with a patient to identify risk for anxiety or depression, and they are also highly interpretable for making policy decisions.

We trained our decision tree classi ers on 80% of the remaining data, holding out 20% for evaluation. We trained and generated trees on several di erent random splits, and the features at each node and the accuracy had minimal changes between each generation. The optimal tree depth was determined using cross validation across 10 folds in a strati ed KFold, and picking the depth where testing accuracy maximizes, before the tree over-trained. The features for user language and country of residence were removed before training to help prevent the decision trees from over tting to the dataset.

6.2.1 Decision Trees with Anxiety

We begin with decision tree that attempts to classify survey participants as Anxious , or Not anxious . A graph of the decision tree depth against the training and testing accuracy is shown in Figure 1. We can see that the optimal depth is 3, which is the highest accuracy achieved before the depth of the tree increases and the training accuracy continues to increase while the testing accuracy remains relatively the same. Therefore, we trained our nal decision tree for anxiety to have a depth of 3.

Figure 3 shows the anxiety decision tree. Each node on the graph contains the likelihood of anxiety, amount of people with high and low anxiety during training, and the majority class at the node. This model had 68.68% accuracy. For reference, in the dataset, 35.78% of participants were Anxious", while 64.22% were Not Anxious". The precision was 64.65%, showing that out of all people that our model labeled with anxiety, 64.65% of people actually had it. 28.08% recall demonstrates that out of everyone with anxiety, our model identi ed 28.08% accurately. The F1 score was .3916 and captures the trade-o between precision and recall. The optimal tree had a small depth and may also be indicative of the limitations of the data. As stated earlier, some of the decisions were also present as consequents in the association patterns for anxiety, so we have con dence that the decisions chosen are statistically signi cant.

Figure 1: Anxiety Depth and Accuracy Graph

The model's accuracy of 68.72% shows signi cant improvement over a naive classi er which classi es all people as Not Anxious , which would have an accuracy of 64.22%. The precision, recall, and F1 scores provide further evidence that the decision tree classi er is picking up on real patterns in the data. While an accuracy of 68.72% may not seem impressive out of context, it is a challenging problem to predict anxiety based on demographic and lifestyle factors, and is unlikely to produce very high accuracy scores. Based on the comparison with a naive classi er, as well as the precision, recall, and F1 scores, we believe this is a successful model.

Figure 2: Depression Depth and Accuracy Graph

6.2.2 Decision Trees with Depression

Figure 2 shows a graph of the decision tree depth against the training and testing accuracy.

We can see that the optimal depth is 4, which is the highest accuracy achieved before training accuracy continues to increase and testing accuracy decreases as the depth of the tree increases. Therefore, we trained our final decision tree for depression to have a depth of 4.

We next consider the decision tree generated to classify participants as "Depressed" or "Not Depressed". Figure 4 displays this tree. This classifier had an accuracy of 67.53%. In the dataset, 41% of participants were "Depressed", while 59% were "Not Depressed". 66.55% precision shows that out of all people that our model labeled with depression, 66.55% of people actually had it. The recall was 42.49% demonstrates that out of everyone with depression, our model identified 42.49% accurately. The F1 score was .5186 and captures the trade-off between precision and recall. However, like the anxiety model, most of the decisions were present in the association rules for depression, so we have confidence that these decisions are statistically significant.

The model predicting depression has an accuracy of 68%, while a naive classifier classifying all people as "Not Depressed" would have an accuracy of 59%. The precision, recall, and F1 scores also indicate that the decision tree classifier is identifying real patterns in the data. Similar to the model predicting anxiety, we believe this is a successful model, given the difficulty of predicting depression from demographic and lifestyle factors.

7 CONCLUSION, DISCUSSION, AND FUTURE WORK

Our findings can help to identify the risk of mental health concerns for individuals in the LGBTQ+ community. Our results could be used for making a simple and interpretable tool that practitioners could use to identify those at increased risk and intervene before anxiety or depression arises. Additionally, these results may provide insight to help policymakers in public health on issues concerning the mental health of individuals in the LGBTQ+ community.

While the association rules mined elucidate useful patterns in their own right, we also tried to use the results of frequent pattern mining for feature selection for our decision trees, by selecting features that appeared in significant patterns. However, for this dataset, it did not have a significant effect on the results of our decision trees. This could be an avenue for future exploration on other datasets.

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Antecedent 1	Antecedent 2	Antecedent 3	Antecedent 4	Anxiety	Conf	Lift	Support
Need bene ts	Universal healthcare	No drug use		Yes	0.3688	1.8974	0.0915
Need bene ts	Citizen	No drug use		Yes	0.3384	1.7408	0.0787
Movement somewhat restricted	Universal healthcare	No drug use		Yes	0.3124	1.6071	0.1038
Movement somewhat restricted	No sex work	Universal healthcare	No drug use	Yes	0.2967	1.5263	0.0833
Citizen				Yes	0.2901	1.4923	0.1372
Universal healthcare	Homosexuality legal			Yes	0.2609	1.3421	0.1238
Has mask access	Universal healthcare	No drug use	Homosexuality legal	Yes	0.2788	1.4344	0.0985
Texting	Citizen	No drug use	Homosexuality legal	Yes	0.2849	1.4656	0.0863
Lower middle				Yes	0.3356	1.7267	0.0856
Single				Yes	0.3153	1.6221	0.1329
Use apps to hook up	Universal healthcare	No drug use	Homosexuality legal	Yes	0.2939	1.5118	0.0819
Emotionally safe	Not lose health insurance	HIV negative	Homosexuality legal	No	0.8369	1.6005	0.0835
Has health insurance	Not lose health insurance	Has mask access	No sex work	No	0.7087	1.3552	0.098
Believes can make positive di erence	Gay	Has mask access		No	0.6389	1.2219	0.0925
Parents are native	Movement somewhat restricted	Trust WHO	Homosexuality legal	No	0.6642	1.2702	0.1371
Video calls	Movement somewhat restricted	Yes	No sex work	No	0.6924	1.3241	0.1137
Citizen	Not cutting meals	No sex work		No	0.7119	1.3614	0.2162
Video calls	Gay	Use apps to hook up	Yes	No	0.6779	1.2963	0.0806
Able to make ends meet	Has sources of hope	No drug use	Homosexuality legal	No	0.7989	1.5278	0.1009
Has health insurance	Low depressed	Parents are native	No sex work	No	0.8989	1.7191	0.1038

Table 2: Anxiety Association Rules

Antecedent 1	Antecedent 2	Antecedent 3	Antecedent 4	Antecedent 5	Dep	Conf	Lift	Support
Emotionally safe	Not lose health insurance	HIV negative	Homosexuality legal		No	0.8185	2.2132	0.0817
Not lose health insurance	Video calls	Movement restricted	No sex work	No drug use	No	0.7087	1.9163	0.0842
Not lose health insurance	Parents are native	Movement restricted	Citizen	Homosexuality legal	No	0.6816	1.8431	0.1005
Has health insurance	Not lose health insurance	Has mask access	No sex work		No	0.6926	1.8728	0.0958
Believes can make di erence	Gay	Has mask access			No	0.6151	1.6632	0.089
Has health insurance	Able to live happy life	Has sources of hope	Gay	Has mask access	No	0.7854	2.1238	0.0792
Video calls	Gay	Citizen	Not cutting meals	Trust WHO	No	0.6798	1.8382	0.0847
Parents are native	Movement restricted	Trust WHO	Homosexuality legal		No	0.6274	1.6965	0.1295
Has health insurance	Able to live happy life	Gay	No sex work	Universal healthcare	No	0.7558	2.0438	0.0796
Video calls	Movement restricted	Yes	No sex work		No	0.6526	1.7648	0.1071
Citizen	Not cutting meals	No sex work			No	0.6735	1.8212	0.2045
Video calls	Gay	Not cutting meals	Has mask access	No sex work	No	0.7063	1.9098	0.088
Gay	Parents are native	Citizen	No sex work	Trust WHO	No	0.6388	1.7273	0.1054
Video calls	Texting	Gay	Yes	Not cutting meals	No	0.7124	1.9265	0.0797
Not lose health insurance	Video calls	Gay	Not cutting meals	Has mask access	No	0.7407	2.003	0.0857
Not lose health insurance	Use apps to hook up	Has mask access	Universal healthcare	Homosexuality legal	No	0.6623	1.7909	0.1008
Has health insurance	Has sources of hope	Citizen	Yes	Homosexuality legal	No	0.7434	2.0102	0.0907
Video calls	Texting	Gay	Citizen	Not cutting meals	No	0.6804	1.8398	0.0951
Healthcare discrimination	Gay	Citizen	Universal healthcare	No drug use	No	0.7286	1.9702	0.0999
Not lose health insurance	Citizen	Not cutting meals	No sex work	Universal healthcare	No	0.7017	1.8975	0.0917

Table 3: Top Lift Depression Association Rules

Antecedent 1	Antecedent 2	Antecedent 3	Antecedent 4	Antecedent 5	Anxiety	Conf	Lift	Support
Gay	Single				Yes	0.3011	1.5489	0.0817
Single	Has mask access	Homosexuality legal			Yes	0.2856	1.4693	0.0845
Universal healthcare	Trust WHO	Homosexuality legal			Yes	0.2985	1.5356	0.0927
Not cutting meals	Trust WHO	No drug use			Yes	0.2472	1.2719	0.0842
Outdoor Space	No sex work	Universal healthcare	No drug use		Yes	0.27	1.3889	0.0866
Movement somewhat restricted	Trust WHO	No drug use			Yes	0.3097	1.593	0.0977
Trust WHO	Homosexuality legal				Yes	0.289	1.4868	0.1126
Outdoor Space	Universal healthcare	Homosexuality legal			Yes	0.2686	1.382	0.0871
Texting	No sex work	No drug use	Homosexuality legal		Yes	0.2718	1.398	0.0781
Single	Has mask access	No drug use			Yes	0.2985	1.5354	0.0873
Has mask access	No sex work	No drug use			Yes	0.2649	1.3627	0.0994
Gay	Has mask access	No drug use			Yes	0.2773	1.4266	0.0929
Citizen	HIV negative	No drug use	Homosexuality legal		Yes	0.2727	1.4028	0.0819
Video calls	Universal healthcare	No drug use			Yes	0.2997	1.5416	0.0888
No drug use	Homosexuality legal				Yes	0.2806	1.4433	0.1414
Parents are native	Use apps to hook up				Yes	0.2828	1.4547	0.0788
Has mask access	No sex work	Universal healthcare	No drug use	Homosexuality legal	Yes	0.2654	1.3654	0.0783
Outdoor Space	No sex work	Homosexuality legal			Yes	0.2461	1.2662	0.0791
Texting	Citizen	Homosexuality legal			Yes	0.2873	1.478	0.0899
Movement somewhat restricted	Trust WHO				Yes	0.3089	1.5891	0.1015

Table 4: Top Lift Anxiety Association Rules

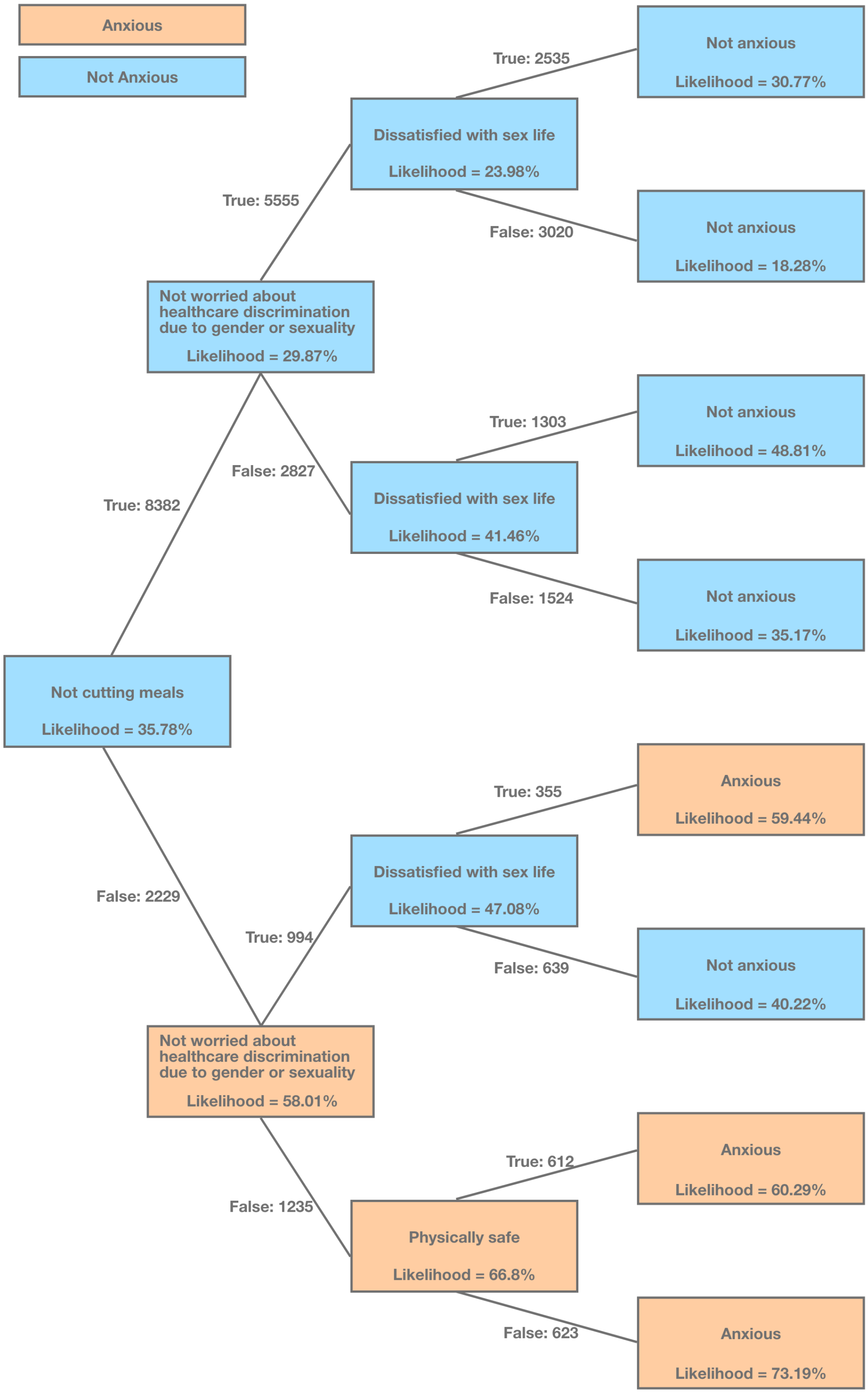

Figure 3: Anxiety Decision Tree