Article

Psychological Health and Drugs: Data-Driven Discovery of Causes, Treatments, Effects, and Abuses

Sarah Alswedani [1], Rashid Mehmood [2,*], Iyad Katib [1] and Saleh M. Altowaijri [3]

[1] Department of Computer Science, FCIT, King Abdulaziz University, Jeddah 21589, Saudi Arabia; sabdullahalswedani@stu.kau.edu.sa (S.A.); iakatib@kau.edu.sa (I.K.)
[2] High-Performance Computing Center, King Abdulaziz University, Jeddah 21589, Saudi Arabia;
[3] Department of Information Systems, Faculty of Computing and Information Technology, Northern Border University, Rafha 91911, Saudi Arabia; Saleh.Altowaijri@nbu.edu.sa (SMA)
* Correspondence: RMehmood@kau.edu.sa;

Abstract: Mental health issues can have significant impacts on individuals and communities and hence on social sustainability. There are several challenges facing mental health treatment, however, more important is to remove the root causes of mental illnesses because doing so can help prevent mental health problems from occurring or recurring. This requires a holistic approach to understanding mental health issues that are missing from the existing research. Mental health should be understood in the context of social and environmental factors. More research and awareness are needed, as well as interventions to address root causes. The effectiveness and risks of medications should also be studied. This paper proposes a big data and machine learning-based approach for the automatic discovery of parameters related to mental health from Twitter data. The parameters are discovered from three different perspectives, Drugs & Treatments, Causes & Effects, and Drug Abuse. We used Twitter to gather 1,048,575 tweets in Arabic about psychological health in Saudi Arabia. We built a big data machine learning software tool for this work. A total of 52 parameters were discovered for all three perspectives. We defined 6 macro-parameters (Diseases & Disorders, Individual Factors, Social & Economic Factors, Treatment Options, Treatment Limitations, and Drug Abuse) to aggregate related parameters. We provide a comprehensive account of mental health, causes, medicines and treatments, mental health and drug effects, and drug abuse, as seen on Twitter, discussed by the public and health professionals. Moreover, we identify their associations with different drugs. The work will open new directions for social media-based identification of drug use and abuse for mental health, as well as other micro and macro factors related to mental health. The methodology can be extended to other diseases and provides a potential for discovering evidence for forensics toxicology from social and digital media.

Keywords: Psychological Health; Drugs; Twitter; Machine Learning; Big Data; Drug Abuse

1. Introduction

Several factors are contributing globally to declining social sustainability including people's health, economic issues, global events such as the COVID-19 pandemic and environmental disasters and increased social division and polarization [1]. These factors have caused negative impacts on the well-being and future prospects of our societies, leading to declining social sustainability. Social sustainability is closely linked to economic and environmental sustainability, as the economic conditions of a society and the state of the natural environment can both have major impacts on the well-being of its members. In order to address the risk of declining social sustainability, it is important to act to address the root causes of these issues.

Mental health is related to social sustainability because it is an important aspect of overall health and well-being, and mental health issues can have significant impacts on individuals and communities. Mental health issues such as depression and anxiety can lead to decreased productivity, absenteeism, suicides, and other negative impacts on social and economic well-being. For example, according to the World Health Organization (WHO), there is a suicide every 40 seconds, totalling more than 700,000 per year. This high rate of suicide highlights the deteriorating social conditions around the world [2].

Moreover, addiction is often related to mental health in that it can be a symptom of, or a response to, underlying mental health issues. For example, people may turn to substances or behaviours such as drugs, smoking, alcohol, gambling, or internet use as a way to cope with mental health issues such as depression, anxiety, or stress. However, addiction can also contribute to or exacerbate mental health problems, as the use of substances or engagement in certain behaviours can have negative impacts on mental well-being. According to the Centers for Disease Control and Prevention (CDC), cigarette smoking causes over 480,000 deaths in the United States annually, with over 40,000 deaths caused by second-hand smoke. The smoking habit has caused serious health problems for over 16 million Americans [3]. The National Survey on Drug Use and Health (NSDUH) also reports that more than 19.5 million Americans over the age of 12 struggle with substance use disorders [4].

There are several challenges facing mental health treatment, including a lack of access to care, stigma, a shortage of mental health professionals, limited treatment options, co-occurring disorders, and a lack of integration with physical health care. These challenges can make it difficult for people to receive the mental health treatment they need, which can have negative impacts on their well-being and overall quality of life. Addressing these challenges is important for promoting mental health and improving the well-being of individuals and communities.

However, more important is to remove the root causes of mental illnesses because doing so can help prevent mental health problems from occurring or recurring, improve the effectiveness of treatment, and reduce the need for ongoing care. Root causes of mental health issues can include trauma, genetics, environmental factors, and physical health issues. Addressing these root causes can promote mental health and well-being and improve the lives of individuals and communities. A multifaceted approach that addresses social, economic, and environmental factors as well as individual needs is needed to remove the root causes of mental health issues effectively.

There is a significant body of research on the relationship between physical and psychological health. Studies have explored the connection between mental stress and physical diseases such as cancer, lung disease, and kidney disease [5]–[7], as well as the impact of physical conditions such as obesity and smoking on psychological health [8]–[10]. There is also research on specific psychological disorders, including depression, anxiety, stress, and post-traumatic stress disorder (PTSD)[11]. In the education field, there is research on the prevalence of psychological illnesses among students and academics and the impact of teachers' mental health on students' achievement [12]. The COVID-19 pandemic has also led to research on the effects of the pandemic on psychological health, including the spread of depression, anxiety, and stress among the general population, as well as the psychological impact of quarantine and social distancing measures [13], [14].

A holistic approach to understanding mental health issues is missing from the existing research. What is needed is to understand mental health and illnesses in the context of socio-economic and environmental contexts, create awareness for the people of the causes and effects of mental illnesses, and develop interventions to bring social behaviors, lifestyle, and root cause changes.

1.1 This Work

This paper proposes a big data and machine learning-based approach for the automatic discovery of parameters (or factors) related to mental health (or psychological health) from Twitter data. The parameters are discovered from three different

 doi:10.20944/preprints202301.0415.v2

perspectives Drugs & Treatments, Causes & Effects, and Drug Abuse. Moreover, we automatically discover associations between the parameters and drugs.

We used Twitter's REST API and the Tweepy library to gather 1,048,575 tweets in Arabic about psychological health in Saudi Arabia during the month of October 2022. The tweets were retrieved using various keywords and hashtags related to mental health. We built a machine learning software tool for this work (see Section 3 for details). A total of 52 parameters were discovered for all three perspectives. We defined 6 macro-parameters to aggregate related parameters. The macro-parameters are Diseases & Disorders, Individual Factors, Social & Economic Factors, Treatment Options, Treatment Limitations, and Drug Abuse.

We provide a comprehensive account of mental health, causes, medicines and treatments, mental health and drug effects, and drug abuse, as seen on Twitter, discussed by the public and health professionals. Moreover, we identify their associations with different drugs. None of the earlier works have reported such a holistic view of mental health. The work will open new directions for social media-based identification of drug use and abuse for mental health, as well as other micro and macro factors related to mental health. The methodology can be extended to other diseases. The methodology also provides a potential for discovering evidence for forensics toxicology from social and digital media. The work presented in this paper is the beginning, many more works are needed to investigate the potential of social media for forensic purposes.

Note that we have used contextual translations and made some adjustments to the translations of original Arabic tweets in order to make them more understandable to English readers. This may include changes to the order of the information in the tweet, the removal of unnecessary or redundant information, and the provision of summaries for tweets that are too long or contain unnecessary information. We have also sometimes omitted parts of the original tweets in order to protect the privacy of the tweeters. Note that Arabic tweets (typically true for any language) tend to be written in an informal style, so a literal translation may not always be clear or convey the intended meaning. Note also that in some tables in the paper, some search terms, or key terms detected by our machine learning models, may appear multiple times. This is because the original terms in Arabic may be different, but their English translations may be identical.

The paper is organized as follows. Section 2 presents a review of the related work. Section 3 explains our methodology and the design of our tool. Sections 4, 5, and 6 explain the discovered parameters from three different perspectives. Section 7 provides a discussion. The conclusion is provided in Section 8.

2. Related Work

This section provides a review of the works related to our paper. Specifically, we review research on the relation between physical illnesses and mental health (Section 2.1), specific mental health disorders and factors (Section 2.2), effects of education on mental health (Section 2.3), CVOID-19 and mental health (Section 2.4), Machine learning in mental health (Section 2.5), and the use of Twitter data in mental health (Section 2.6). Our intention in this section is not to be extensive but to provide a brief account of research in areas that are relevant to our research.

2.1 Physical Illnesses

A good part of research on psychological health have investigated the relationship between psychological illnesses and chronic physical diseases (e.g., cancer, lung, and kidney diseases) using different data sources. For instance, Schächinger et al. [5] examined the impact of mental stress on pulmonary circulation in both health and sickness using clinical data. They found that in patients with severe pulmonary hypertension, mental stress increases right heart afterload. Volpato et al. [6] presented an analysis of the research works focusing on the associations between anxiety, depression, and adherence in chronic obstructive pulmonary disease (COPD) patients. Altuntaś et al. [7] studied the chronic thyroid-stimulating hormone suppression's effects on psychological health and sleep quality in patients with thyroid cancer. Hagger et al. [16] examined the psychological health of young persons with diabetes in Australia.

Studies have also been conducted on investigating the connection between obesity and mental health. Rodriguez-Ayllon et al. [8] investigated the relationships between psychological well-being and psychological distress in adolescents who are overweight or obese. Tubbs et al. [9] looked into the bivariate association between obesity, psychopathology, and sleeping problems.

Some studies have looked into relationship between smoking and psychological diseases. Taylor et al. [10] investigated the relationship between smoking, quitting smoking, and mental health. Schmidt et al. [17] examined the relationship between average patterns of psychological health and average patterns of smoking using longitudinal data.

2.2 Specific Disorders and Factors in Psychological Health Research

Many works have investigated psychological diseases with a focus on specific factors or disorders such as depression, anxiety, stress, and post-traumatic stress disorder (PTSD). Wang et al. [18] proposed a model for detecting depression with a focus on the attributes of depression in the content of micro-blogs in Chinese. Bremner [19] investigated the effects of traumatic stress on the brain including the hippocampus, and prefrontal cortex. Jing et al. [11] studied post-traumatic stress disorder (PTSD) among Chinese residents of various flood zones in Henan Province with the aim to provide fundamental knowledge for developing measurement strategies to enhance the psychological protection and anti-stress capacity of the residents after the disaster. Other works on the subject of this section include investigating anxiety disorder and treatment preference [20] the relationship between stress and anxiety on the neurobiological level [21], and Schizophrenia prediction using clinical data [22].

2.3 Education and Psychological Health

Researchers have investigated the prevalence of psychological illnesses in students and academics. For instance, Çelik et al. [23] looked into the incidence of depressive symptoms among health sciences students as well as the quality of their sleep and several other connected issues. They found that depression is more common in students who struggle academically and financially, use alcohol or tobacco, have chronic illnesses, or have mental health issues. Other works on the subject of this section include investigating anxiety levels of urban and rural areas [24], anxiety and depression among medical students [25], [26], the impact of teachers' math anxiety on students' achievement [12], the association between depression and burnout among school teachers [27], the relationships between teachers' self-perceived depression, stress, and emotional exhaustion and potential predictors of their psychological well-being, such as professional background and teaching efficacy [28].

2.4 COVID-19 and Psychological Health

Researchers have also explored the effects of COVID-19 on psychological health. Salari et al. [13] presented an analysis of research studies related to the spread of depression, anxiety, and stress among the general population during the pandemic of COVID-19. A systematic review and a comprehensive meta-analysis were performed on articles related to stress and anxiety, during the pandemic. Zhang et al. [14] provided cross-sectional research on the psychological effects of COVID-19 on Chinese adolescents including anxiety, depression, and stress. Gianfredi et al. [29] reviewed the research articles studying the mental effects of COVID-19 epidemic through the patterns found in internet searches.

Several works studied psychological effects of COVID-19 pandemic on students and the education sector. Ding et al. [30] studied the mental health of English teachers during the outbreak of coronavirus. Huckins et al. [31] investigated whether the behavioral patterns and mental health of students in college have changed in response to the pandemic of COVID-19 and whether these changes are associated with news related to COVID-19. Zhou et al. [32] provided a cross-sectional study that investigates the prevalence rates of depression and anxiety, as well as their socio-demographic correlation, among Chinese high school students between 12–18 years who got affected by the COVID-19 pandemic. Alswedani et al. also reported evidence for psychological stress among students, educators, and parents during COVID-19 [33], [34]. Other studies that reported psychological effects of COVID-19 include [35], [36].

2.5 Machine Learning Methods in Psychological Health

We used machine learning in this paper and therefore we review works on the use of machine-learning methods in studying topics related to mental health. For instance, Iram et al. [37] utilized random forests algorithm to distinguish between linguistic styles, detect depressive and non-depressive contents, and identify the degree of severity among contents on social media. Islam et al. [38] used various ML algorithms such as Decision Tree classifier, SVM, and KNN for depression detection on Facebook. They examined four forms of factors of depression including the emotional, temporal, and linguistic style. Wang et al. [39] used sentiment analysis models for detecting depression in micro-blogs.

2.6 Twitter Data in Psychological Health Research

Several studies have utilized Twitter data for studying psychological health. Zhang et al. [36] developed a pipeline to monitor the trends of depressive users and analyzed depression levels. Fatimah et al. [40] used tweets posted by Tweeters from Indonesia to detect anxiety and other psychological issues. Some works have focused on the detection of specific psychological illnesses from posted tweets such as depression detection [41], [42], and detection of post-traumatic stress disorder [43]. Roy et al. [44] investigated the effects of the cannabis drug on psychological health.

Tweets in the Arabic Language: We found only a few works on mental health using Twitter data in Arabic. Alabdulkreem [45] proposed a deep-learning technique to predict depressive and non-depressive Arabic tweets in Saudi Arabia. Almouzini et al. [46] proposed a supervised predictive model to detect depression among Twitter posts in the Gulf region using sentiment analysis.

2.7 Research Gap

Our work differs from previous research studies from a variety of perspectives including its particular focus, the nature of the dataset (data size, language, time period, geography), the software design (the pipeline and approach for machine learning), the innovative methodology of using AI for discovering parameters, and the innovative methodology and design of finding associations between parameters and drugs.

3. Methodology and Design

In this section, our methodology and the design of our tool are explained. Figure 1 depicts the proposed system architecture. The architecture consists of five modules: data collection and storage, data preprocessing, parameter discovery, validation, reporting and visualization. These modules will be covered in the subsequent sections. The methodology overview of the proposed tool will be discussed in Section 3.1. The architecture's modules will be discussed in Section 3.2-3.6.

3.1 Methodology Overview

The purpose of this study is to develop an artificial intelligence (AI) approach for automatically detecting and identifying psychological diseases, diseases' causes & effects, and drug abuse. In this study, we focus on psychological disorders in Saudi Arabia by analyzing tweet data in Arabic. However, the proposed approach can be applied to a wide range of diseases regardless of language.

There are five components in the proposed approach: data collection & storage, data preprocessing, drugs for psychological health parameters discovery, validation, and visualization & reporting. Our first step was to use a Python script with a specified search query and a set of keywords and Twitter hashtags related to psychological health in Saudi Arabia (See Table 1). Tweets were saved in JSON format and then converted to XLXS format. After that, in the preprocessing component, stop words were eliminated from the text using Natural Language Toolkit (NLTK) and dialectical Arabic stop word lists (For more details see Section). A discovery module was then constructed for data analysis and detection of parameters using Latent Dirichlet Allocation (LDA) and the scikit-learn library. We discovered the parameters from three different perspectives (Drugs & Treatments, Causes & Effects, and Drug Abuse). Each perspective is discussed in detail in Sections 4-6. The discovered parameters are then presented visually through an intertopic distance map, keyword frequency diagrams (corpus-wide and cluster-specific), and parameter temporal progression. The maps and term frequency diagrams were computed and plotted using the PyLDAvis tool [47]. Finally, the results were validated internally and externally. The discovered parameters were validated internally by finding tweets that supported them. Several online newspapers and reports were used to validate the parameters externally.

3.2 Data Collection

We collected Arabic tweets that are related to psychological health in Saudi Arabia using Twitter REST API and Tweepy. The data was obtained using various key terms and hashtags related to psychological health. For instance, the following key terms were used: "اكتئاب" (Depression), "الحزن" (Sadness), "الهلع" (Panic), "الأمراض العقلية" (Mental Illness), and others. Additionally, we used various hashtags such as "#شهر_الاكتئاب" (Depression Month), "#القلق_الاجتماعي" (Social Anxiety), "#الرهاب الاجتماعي" (Social Phobia), and others. A sample of the keywords and hashtags that were used for data collection is provided in Table 1. The list of Arabic key terms used in data collection can be found here [15]. The data was collected from the 1st to the 31st of October 2022. Approximately, 1,048,575 tweets have been obtained. Tweets were retrieved from Twitter as JSON (JavaScript Object Notation) objects. Every tweet involves several attributes such as "full_text", "created_at", "id", "place", and "geo". After that, we extracted these attributes and saved the result in an XLSX file. Duplicate tweets were removed based on Tweet “Id”.

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 27 February 2023 doi:10.20944/preprints202301.0415.v2

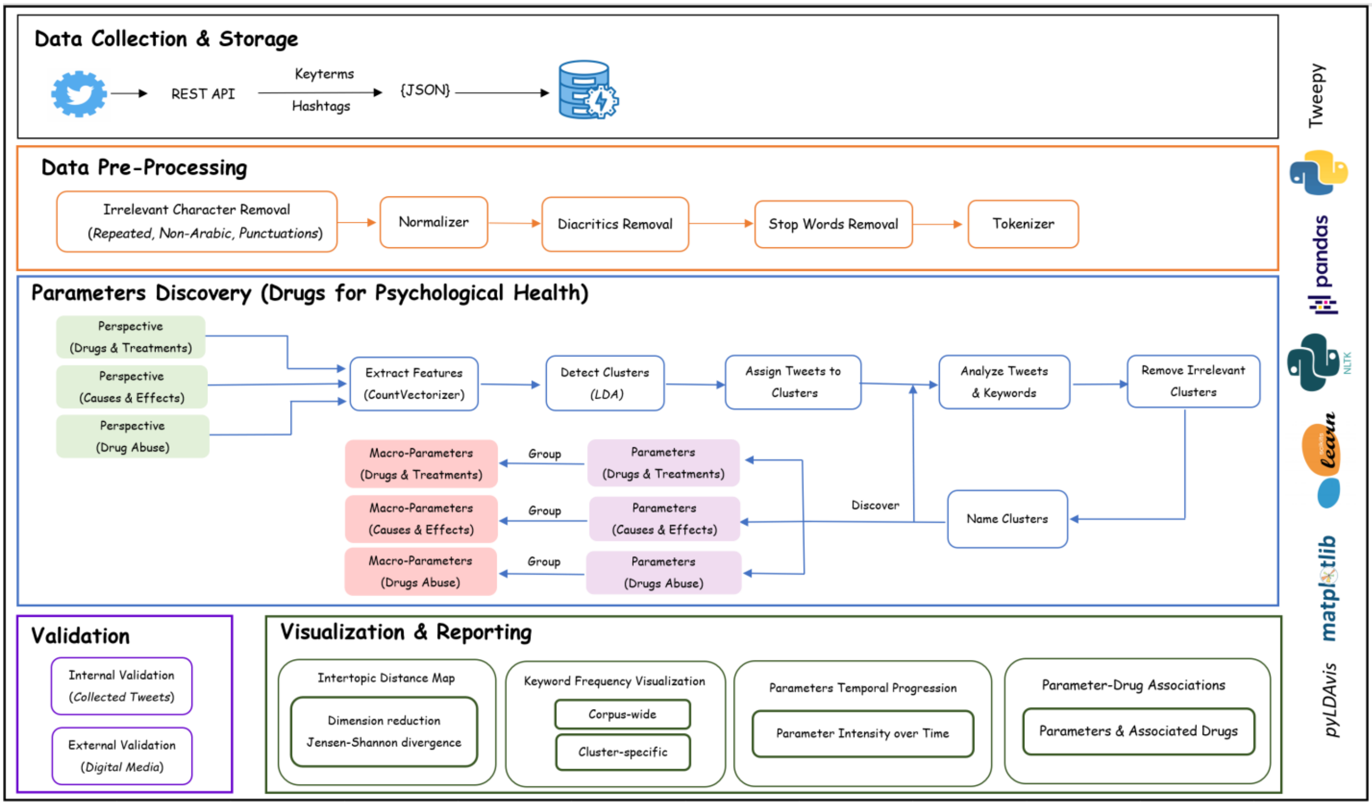

Figure 1. System Architecture

Table 1. The Keywords and Hashtags used for Dataset Collection

Keywords
انتحار، رهاب اجتماعي، اكتئاب، كآبة، مكتئب، مكتئبة، المكتئبين، الحزن، خوف، القلق، الوسواس، الرقية، الحسد، الهلع، أعصاب، العلاج النفسي، الصحة النفسية، استشارة نفسية، الأمراض النفسية، الصحة العقلية، الأمراض العقلية
Suicide, Social Phobia, Depression, Depressed, depressed, depressed, Sadness, Fear, Anxiety, Obsessive, Incantation, Envy, Panic, Neurology, Psychotherapy, Mental Health, Psychological Counseling, Mental Illness, Mental Health, Mental Illness
Hashtags
اليوم_العالمي_لمنع_الانتحار، #شهر_التوعية_لمنع_الانتحار، #منع_الانتحار، #القلق_الاجتماعي، #الرهاب الاجتماعي، #اكتئاب، #شهر_الاكتياب، #شهر_الاكتئاب، #الإكتئاب_الموسمي
World Suicide Prevention Day, Suicide Awareness Month, Suicide Prevention, Social Anxiety, Social Phobia, Depression, Depression Month, Seasonal Depression

3.3 Data Pre-Processing

Data analytics requires the preparation of data as a critical ingredient. Data preprocessing involves a number of methods for cleaning, eliminating noise, improving quality, and eventually, increasing accuracy. One of the libraries available for preparing textually based data is Natural Language Toolkit (NLTK). Preprocessing includes a number of steps, including tokenization, normalization (replacing letters), stop word removal, and the elimination of irrelevant words and characters. Our first step in the preprocessing was eliminating all irrelevant characters and words such as numbers, URLs, different symbols (e.g., &, @, and #), English alphabets, emojis, etc. Moreover, we eliminated non-Arabic characters, repeating characters, and all various forms of punctuation symbols such as brackets and mathematical notations. The next step was tokenization and normalization in which we removed all different types of Arabic diacritics including single marks such as (◌َ), Damma (◌ُ), Kasra (◌ِ), Tashdid (◌ّ), and Sukun (◌ْ), as well as double marks such as Tanwin Damm(◌ٌ), Tanwin Kasr (◌ٍ), and Tanwin Fath (◌ً). Moreover, we used the normalizer to convert all different shapes of Alif (آإ) , Yaa (ي), and Taa Murbutah (ة) to the basic form bare Alif (ا), dotless Yaa (ى), and Haa (ه), respectively. After that, we removed the list of stop words provided by NLTK library with an additional list of words in dialectical Arabic developed by us; further details can be found in [33].

3.4 Parameters Discovery

In this section, we discuss the methodology for identifying psychological health parameters through topic modeling analysis of Twitter data. Modeling of topics is a frequently employed AI approach for data analysis and topic discovery, and it contains various algorithms that identify patterns and themes in a collection of documents by clustering word terms [48]. For topic modeling, one popular unsupervised learning approach is the Latent Dirichlet Allocation (LDA) algorithm. It is a statistical technique for determining the topics that come up most frequently in a group of documents. It works on mapping a group of documents (such as tweets) into a group of themes or clusters, assigning each document a certain likelihood of being related to a specific topic. The parameter discovery was implemented on Google Colab platforms using various Python packages such as Scikit-Learn, Numpy, and Pandas.

We modeled the data from three perspectives: Drugs & Treatments, Causes & Effects, and Drug Abuse. We used a list of keywords to create a subset of the dataset and discover the parameters for each perspective. For instance, for the Drugs & Treatments perspective, we used antidepressant, painkiller, and medicine names (e.g., Panadol). For the Causes & Effects perspective, we used multiple keywords such as side, effects, and cause. For Drug Abuse perspective, we used multiple keywords such as abuse and extra. See Tables 2, 5, and 8 for the complete list of the keywords. Most of the keywords are in Arabic and few in English because some tweets use some terms in English such as medicine names. We modeled each perspective into different clusters. After extracting the clusters, we allocated each tweet to its cluster based on the highest probability of the tweet association with a cluster. After that, we performed an analysis of the tweets and keywords in each cluster in which we looked at the keyworks and examined the context of the keywords in each parameter. This enabled us to name each cluster based on the keywords and tweets using our domain knowledge. We iteratively refine clusters' names using our domain knowledge and other quantitative measures. The process enabled us to eliminate irrelevant clusters and combine clusters that were similar. We eventually aggregated the parameters based on their common themes into macro-parameters which are representing broader areas. This is done separately for each perspective.

3.5 Validation

The discovered parameters were validated internally and externally. For external validation of the data and parameters extracted from the Twitter data, we utilized academic papers, news articles, and online reports. To assess the validity of the discovered data and parameters, internal validation was carried out utilizing tweets from the gathered dataset.

3.6 Visualization & Reporting

In this study, we provide a variety of visualization methods of the parameters we have discovered. These are intertopic distance maps, taxonomies, as well as keyword frequency diagrams (both cluster-specific and corpus-wide). Python pyLDAvis package was used to compute and depict the terms frequency diagrams and distance maps [48], [49]. The intertopic scaling and distances were computed utilizing the Jensen-Shannon divergence. The width of the bars in the diagrams of keyword frequency represents the

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 27 February 2023 doi:10.20944/preprints202301.0415.v2

frequency distributions at the topical and corpus levels, respectively. Matplotlib was one of the other Python libraries we used.

4. Parameter Discovery for Psychological Heath (Drugs & Treatments)

This section focuses on the parameters discovered for the Drugs & Treatments perspective. Section 4.1 presents an overview of parameters and macro-parameters. Sections 4.2-4.6 explain the parameters in detail. The associations between the detected parameters and drugs are provided in Section 4.7.

As noted in the Introduction section, we have translated the Arabic content (words and tweets) contextually and made adjustments to the original text, including changes to the information order and the removal of unnecessary or redundant information. We have also omitted parts of the original text that were not useful.

4.1 Overview and Taxonomy

As explained earlier, the data was modeled from three perspectives. In this section, we focus on the Drugs & Treatments perspective. We used a list of keywords to create a subset of the dataset and discover the parameters for that perspective. The list contains Arabic keywords and some English keywords because some tweets use some terms in English such as medicine names. The translation of the list of keywords used is provided in Table 2. Note that in Table 2 some search terms appear multiple times. This is because the original terms in Arabic are different, but their English translations are identical. The dataset that we got after filtering the data contains 6,717 tweets.

The Latent Dirichlet Allocation (LDA) modeling algorithm detected 30 clusters from the subset of the dataset. We merged similar clusters based on the domain knowledge and some quantitative approaches; the parameters were categorized into five macro-parameters. The methodology and process for discovering and grouping macro-parameters were discussed in Section 3.

Table 2. Keywords Used to Discover Parameters (Perspective: Drugs & Treatments)

Keywords Used to Discover Parameters (Drugs & Treatments Perspective)
الدواء، أدويه، أدوية، الادوية، دوائي، صرف، وصفة، جرعة، مضاد اكتئاب
medicine, medicine, drugs, pharmaceutical, medicinal, prescribe, prescription, dose, antidepressant
كمضاد، مضادات، مهدئات، ملجم، ميلليجرام، مليجرام، حبة، حبات، حبوب، مسكن
as anti (depression), anti (depressants), tranquilizer, milligrams, milligrams, milligrams, pill, pills, pills, reliever
بنادول، بندول، روفيناك، سليبريكس، إيبوبروفين، أسيتامينوفين، برينتيليكس، الدولوكستين، فافرين، السيروكسات، ليركا
Panadol, Panadol, Rufenac, Celebrex, Ibuprofen, Acetaminophen, Brintellix, Duloxetine, Faverin, Seroxat, Lyrica
ريميرون، سبرالكس، سيبرالكس، سيبراليكس، زاناكس، زنكس، البنزوديازيبين، الڤاليوم، فاليوم، إسيتالوبرام، ليبونكس
Remeron, Cipralex, Cipralex, Cipralex, Xanax, Xanax, Benzodiazepine, Valium, Valium, Escitalopram, Leponex
باروكستين، بوبروبيون، الايميبرامين، هالوبيريدول، ريزيربين، تيترابينازين، الكلونازيبام، اللورازيبام، الديازيبام
Paroxetine, Bupropion, Imipramine, Haloperidol, Reserpine, Tetrabenazine, Clonazepam, Lorazepam, Diazepam
أميتريبتلاين، اميتريبتلاين، أميتربتيلين، نورتريبتيلين، ميرزاجن، بروزاك، السيروتونين، سيبروهيبتادين، سالیباكس
Amitriptyline, Amitriptyline, Amitriptyline, Nortriptyline, Mirzagen, Prozac, Serotonin, Cyproheptadine, Salipax
الترامادول، سيرتون، سيروتونين، ميلاتونين، ويلبوترين، ليتروزول، كابيرغولين، ترانيلسيبرومين، قو مود
Tramadol, Serotonin, Serotonin, Melatonin, Wellbutrin, Letrozole, Cabergoline, Tranylcypromine, Gomood
الرديولا، الروديولا، الاشواغاندا، الاشواجاندا، الاشواجندة، دسبتالين، امبرازول، أوميبرازول
Rhodiola, Rhodiola, Ashwagandha, Ashwagandha, Ashwagandha, Duspatalin, Omeprazole, Omeprazole

Table 3 provides a list of the detected parameters for the Drugs & Treatment perspective. Column 1 lists the macro-parameters. A total of five macro-parameters are present, including Diseases & Disorders, Individual Factors, Social & Economic Factors, Treatment Options, and Treatment Limitations. The second column presents twenty-four

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 27 February 2023 doi:10.20944/preprints202301.0415.v2

parameters. Some of the parameters that are related to one another are merged. The parameters' IDs are provided in the third column. In Column 4, the keywords' percentage of the parameters are presented. The top 20 keywords related to each parameter are listed in the fifth column. For English readers to better grasp the context of the terms, these keywords and additional Arabic content (for instance, tweets, etc.) were contextually translated.

Table 3. Macro-Parameters and Parameters (Perspective: Drugs & Treatments)

Macro-Parameter	Parameters	ID	(%)	Keywords
Diseases & Disorders	Postpartum Depression	29	2	الاكتئاب، حاله، الولاده، كابه، الموت، تختلف، خصوصا، اكتئاب، بادويه، الام، تصىب، النساء، عاده، الحزن، الزوج، نصح، تكره، النفاس، تدعى، الاولى depression, state, birth, gloom, death, different, especially, depression, medicine, mother, afflict, women, usually, sadness, husband, advise, hate, postpartum, called, first
Individual Factors	Anxiety	14	3.1	ادويه، قلق، اكتئاب، النفسه، الاكتئاب، النفسى، ممكن، دكتور، حد، الادويه، نعمه، الوسواس، القهرى، بنام، الام، علاجه، عظىمه، الصحه، الكتاب، جرعه medicine, anxiety, depression, psychological, depression, psychological, possible, doctor, limit, pharmaceutical, blessing, obsessive-compulsive disorder, sleep, pain, treatment, great, health, book, dose
	Sadness	18	2.8	الاكتئاب، العلاج، الحزن، زمان، النفسى، مضادات، الاعراض، النفسه، فكىف، حبوب، علاج، تعجب، عمىق، خابت، امانىنا، الجرح، ففى، بعد، نفسه، شفى depression, treatment, sadness, time, psychological, anti (depression), symptoms, psychological, how, pills, treatment, wonder, deep, disappointed, hopes, wound, in, re-in, psychiatric, heal
	Poor Concentration	19	2.8	الاكتئاب، الادويه، ادويه، علاج، اضطراب، مضادات، النفس، اسباب، حبوب، السكر، كثىر، نقص، القلق، وصفه، الامراض، الحمدلله، العلاج، النفسه، اكتئاب، خطىر depression, pharmaceutical, medicine, treatment, disorder, anti (depression), self, causes, pills, diabetes, a lot, deficiency, anxiety, prescription, diseases, praise be to God, treatment, psychological, depression, dangerous
	Poor Memory	10	3.6	الاكتئاب، الذاكره، دواء، مضاد، حبوب، المرىض، الدماغ، سبب، مضادات، جرب، لانه، وغىره، ضعف، التركىز، مهم، وسبب، اخطر، بانه، تدرى، والاثار depression, memory, medicine, anti (depression), pills, patient, brain, cause, anti (depression), try, because, others, weakness, concentration, important, cause, dangerous, that, unknowingly, effects
	Loss of Appetite	27	2.4	بسكوت، النفسى، العلاج، ادويه، الاكتئاب، اكل، حاجه، باخد، لوحده، خفىف، اولا، قعدت، فا، رقم، القهوه، الشوكولاته، فود، عظىم، منازع، جنب biscuits, psychological, treatment, medicine, depression, eat, thing, take, alone, light, first, sat, in, number, coffee, chocolate, food, great, dispute, side
	Fear of Medicine	3	5.1	خوف، ادويه، حاجه، طول، اخد، عقلى، شدىد، رحت، قررت، افكار، حاسس، دلوقتى، وعندى، هاخد، ومفىش، خطوه، المساعده، لمشاعر، بالعافىه، للاخر fear, medicine, need, length, take, mind, intense, went, decided, thoughts, feelings, now, have, take, no, help, feelings, wellness, end
Social & Economic Factors	Poverty	26	2.5	حزن، بقول، صرف، الالم، كمىه، اولادى، والدموع، تحكى، المعاش، اتنشل، منتظرىنى، تحمل، الادويه، الامراض، الاكتئاب، النفسه، خوف، مسكن، قوى، النفسى sadness, say, receive, pain, quantity, children, tears, tell, pension, stolen, waiting, bear, medicines, diseases, depression, psychological, fear, dwelling, strong, psychological
	Unemployment & Insufficient Finances	2	6.5	مره، اكتئاب، حبوب، طىب، للاسف، عمل، صعبه، السلام، حاله، مساعده، تعبت، حاولت، ورحمه، وبركاته، السجن، عىال، انتحر، اجىب، وعندى، باحث once, depression, pills, good, unfortunately, work, difficult, peace, condition, help, tired, tried, mercy, blessings, prison, sons and daughters, suicide, bring, have, seeker
	High Cost of Healthcare	4	4.2	امى، اكتئاب، التفكىر، اقسم، العظىم، تكفون، ىخلىكم، وسكر، سدادها، تدفعه ادويه، عاجزه، وماتنام، الكهرباء، ودخلها الضمان، ومرىضه، فضىق، ارمله كبىره السن، فرحوها، حاد وضغط، فاتوره mother, depression, thinking, swear, great, please, keep, diabetes, pay, pay her medication, incapacitated, sleep, electricity, income, sick, tightness, elderly widow, cheer, hypertension, bill
	Loss of Loved Ones	21	2.8	حبوب، الاكتئاب، فتره، شعور، فقدت، اهم، للاكتئاب، افضل، للنوم، الامر، الدواء، وحتى، بالحىاه، عاىشه، وفاه، صدىقه، رغبتى، لقد، انىستا، زوجتى pills, depression, period, feeling, lost, most important, depression, best, sleep, matter, medicine, even, life, living, death, friend, desire, I, Iniesta, wife

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 27 February 2023 doi:10.20944/preprints202301.0415.v2

	Forensic Psychiatry	24	2.7	النفسى، الطب، العلاج، والعلاج، الطبيب، للمرضى، الم، خدمات، مرتبط، اضافه، بعلم، توفر، كفاءه، تسهيل، كالادويه، التفاعل، تخص، للمحاكمه، يشتمل، كتحديد psychiatry, medicine, treatment, and treatment, doctor, patients, pain, services, related, addition, knowledge, provision, efficiency, facilitation, medication, interaction, pertaining, trial, including, specifically
	Social Depression	22 25	2.8 2.6	الاكتئاب، الادويه، اكتئاب، عنده، الناس، يبقى، علاج، مريض، النفسيه، الوزن، باخد، العلاج، ادويه، مضادات، اكبر، الحياه، المدينه، زياده، امتى، الضغوط depression, pharmaceutical, depression, has, people, stay, treatment, sick, psychological, weight, take, treatment, medication, anti (depression), bigger, life, city, increase, when, stress
Treatment Options	Walking	15	3.1	صرف، الجسم، المشى، السلبيه، النفسيه، الطاقه، الطبيعيه، قلق، يحتاج، الادويه، الامراض، خوف، يعادل، يعمل، المسكنات، تفريغ، الاندروفين، المهدئه، يفرز، يقلل prescribe, body, walking, negativity, psychological, energy, nature, anxiety, needs, pharmaceutical, diseases, fear, equivalent, work, painkillers, emptying, endorphins, sedatives, secrete, reduce
	Optimism	17	2.9	وسط، السعاده، الحزن، الهم، الليل، العين، محل، الماء، ظما، يجعلها، للعبور، الرعد، سواد، جسرا، وظلمه، والبصر، فاصنع، ينبت، والكدر، البياض midst, happiness, sadness, worry, night, eye, place, water, thirst, make, cross, thunder, blackness, bridge, darkness, sight, make, grow, chagrin, whiteness
	Good Company	16	3	اكتئاب، مضاد، افضل، الصديق، مضادات، الاكتئاب، عادى، ممكن، وبعدها، بتبقى، بتعمل، الفل، صغير، عيب، الدور، الخامس، شغلك، بتاخدها، وتبقى، مقدمات depression, anti (depression), best, friend, anti (depressants), normal, possible, and then, remains, do, good, small, defect, floor, fifth, job, take, remains, introductions
	Pendulum Technique	28	2.3	خوف، بعدها، سؤال، بندول، بنفسك، فعاليه، تعرف، الاجابه، اكتب، اسال، مشاعرك، تعلق، مستعد، بالمنشن، اجابته، حاد، انوى، الاكتئاب، مضادات، الشمس fear, then, question, pendulum, yourself, effectiveness, know, answer, write, ask, feelings, attachment, ready, mention, answer, sharp, intention, depression, anti (depressants), sun
	Spirituality	1 23 30	6.9 2.7 1.5	القلب، خوف، حق، وادويه، الدنيا، قلب، انه، يشتغل، التوكل، الذكر، بالخير، رحم، تتسلل، ينقطع، الرخيصه، ملل، بصيبه، الاكتئاب، ومادام، تيار heart, fear, right, medicine, world, heart, it, work, trust, remembrance, goodness, womb, infiltrate, cut off, cheap, boredom, affliction, depression, and as long as, stream
	Antioxidants	11	3.5	القهوه، النفسيه، الاكتئاب، الاكسده، العلاج، مضادات، الحاله، الناس، يساعد، معظم، المزاجيه، تخفيف، وتحسين، البسيط، بمضادات، غنيه، الفواكه، مجتمعه، علاوه، والخضراوات coffee, psychological, depression, oxidation, treatment, anti (depression), condition, people, helps, most, moods, relieve, improve, simple, anti (oxidants), richness, fruits, combined, plus, vegetables
	Painkillers & Antidepressants	7	3.6	الاكتئاب، ادويه، مرض، العلاج، المريض، النفسى، الدواء، الادويه، نفسى، مضاد، بدل، طبيب، اكتئاب، لمريض، سيبرالكس، المسكن، جسمه، تدى، سلبريكس، بيوجعه depression, medicine, disease, treatment, patient, psychiatric, medication, pharmaceutical, psychological, anti (depression), instead of, doctor, depression, for a patient, Cipralex, painkiller, body, give, Celebrex, hurt
	Community-Supported Therapies	9	3.6	الامراض، النفسيه، مجموعه، وعدم، المجتمع، حياه، تتداخل، الايمان، يعانى، الدواء، وصمه، عوامل، العوامل، نقص، وراثيه، صحى، ولهذا، يتطلب، ودعم، الرياضه diseases, psychological, group, lack of, society, life, interfering, faith, suffer, medicine, stigma, factors, the factors, deficiency, hereditary, healthy, therefore, requires, support, sport
	Psychotherapy & Medication	6 13	3.9 3	النفسيه، الادويه، علاج، النفسى، العلاج، الامراض، الاكتئاب، نفسيه، الصحه، سلوكى، ادويه، الطبيب، نفسى، دوائى، دواء، المرض، الدواء، مرض، بالادويه، النفسيين psychiatric, pharmaceutical, treatment, psychiatric, treatment, diseases, depression, psychological, health, behavioral, drugs, doctor, psychiatric, medicinal, medicine, disease, drug, illness, pharmaceutical, psychiatrists
Treatment Limitations	Antidepressant Limitations	5	4	الاكتئاب، ادويه، الحقيقه، تخفف، الواقع، نفسك، لكنها، الطبيعى، طوال، التعامل، عقلك، لذا، الازمات، وتلك، حقها، مبالغه، اسعاد، الانفعال، السعاده هذا، العصبيه وتساعدك depression, medicine, truth, relieve, reality, yourself, but, natural, throughout, dealing, mind, so, crises, those, right, exaggerating, delight, emotion, happiness, nervousness, help
	Negative Effects of Antidepressant	8 20 12	3.6 2.8 3.4	الاكتئاب، ادويه، اكتئاب، مضادات، الادويه، افضل، ناس، النفسيه، الحزن، الدواء، ممكن، حبه، الحاله، نفسى، فعلا، مرض، الامراض، يوجد، العصبيه، تسبب depression, medicine, depression, anti (depressants), medicines, best, people, psychological, sadness, medicine, possible, pill, condition, psychological, actually, disease, diseases, there is, nervousness, causes

A taxonomy (see Figure 2) illustrating the Drugs & Treatments perspective was created using the parameters detected by our software. The parameters and their macro-parameters are displayed in the taxonomy. The macro-parameters Diseases & Disorders, Individual Factors, Social & Economic Factors, Treatment Options, and Treatment Limitations are represented at the first level. Second-level branches display the discovered parameters such as anxiety, sadness, poor concentration, etc.

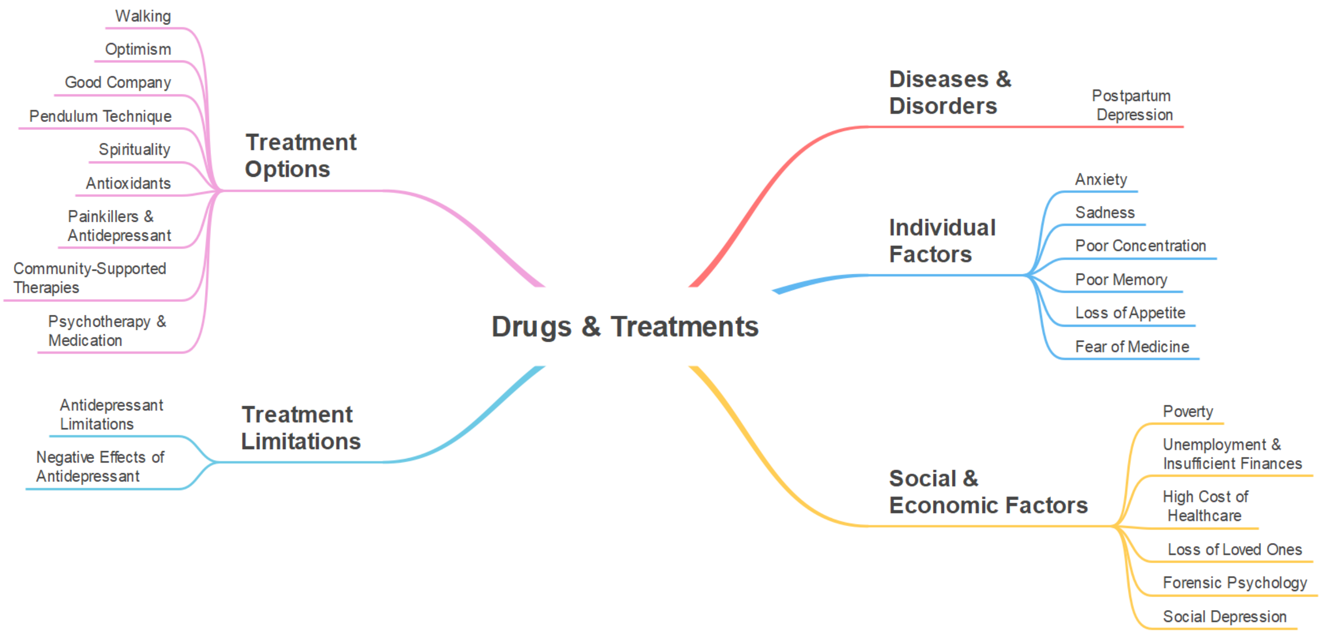

Figure 2. Taxonomy (Perspective: Drugs & Treatments)

Figure 3 presents the Intertopic Distance Map and the overall term frequency of the top 30 keywords for the dataset of the Drugs & Treatments perspective.

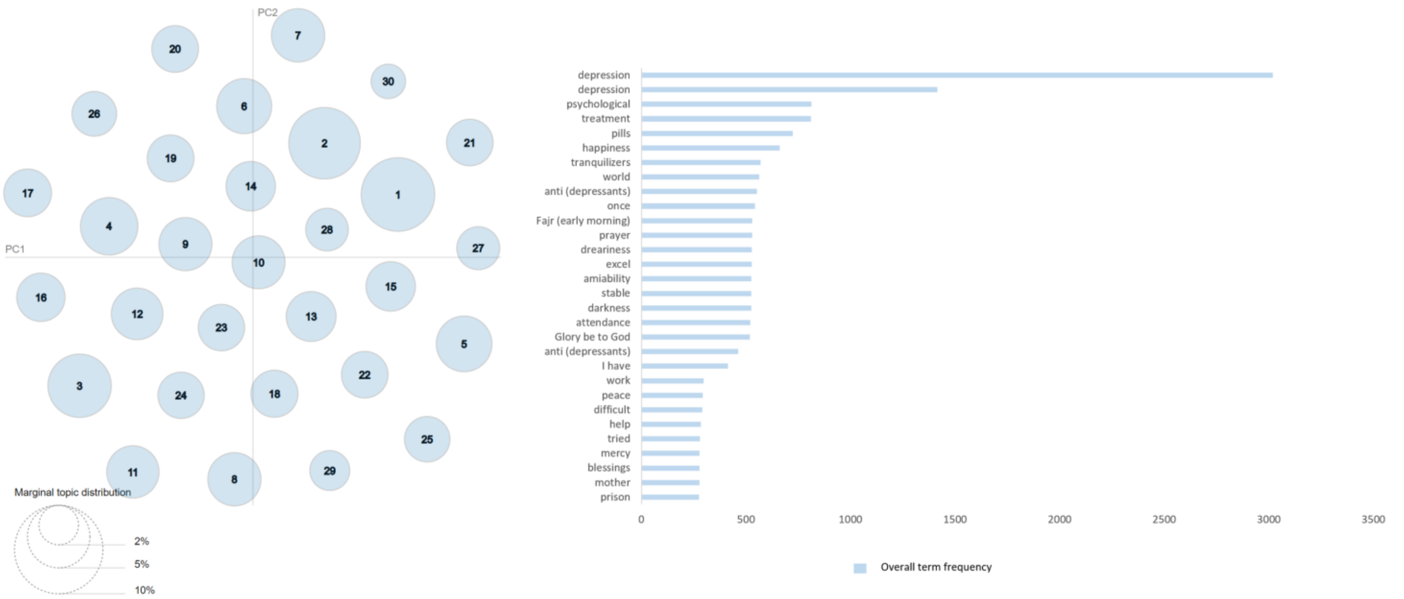

Figure 3. The Intertopic Distance Map of the parameters

 doi:10.20944/preprints202301.0415.v2

4.2 Diseases & Disorders

In this section, we discuss the parameters related to the macro-parameter Diseases & Disorders. Figure 4 shows the ten top key terms according to term frequency (for further details see Section 3.6).

4.2.1 Postpartum Depression

This parameter is about postpartum depression which is a form of depression develops in women after giving birth to a child. The parameter is represented by keywords such as depression, birth, gloom, death, mother, afflict, women, sadness, husband, hate, and postpartum. Several tweets in this parameter discuss the symptoms of this diseases such as exhaustion and lack of energy, sleep disturbance, anorexia disorder, weakness in concentration, and thinking about death.

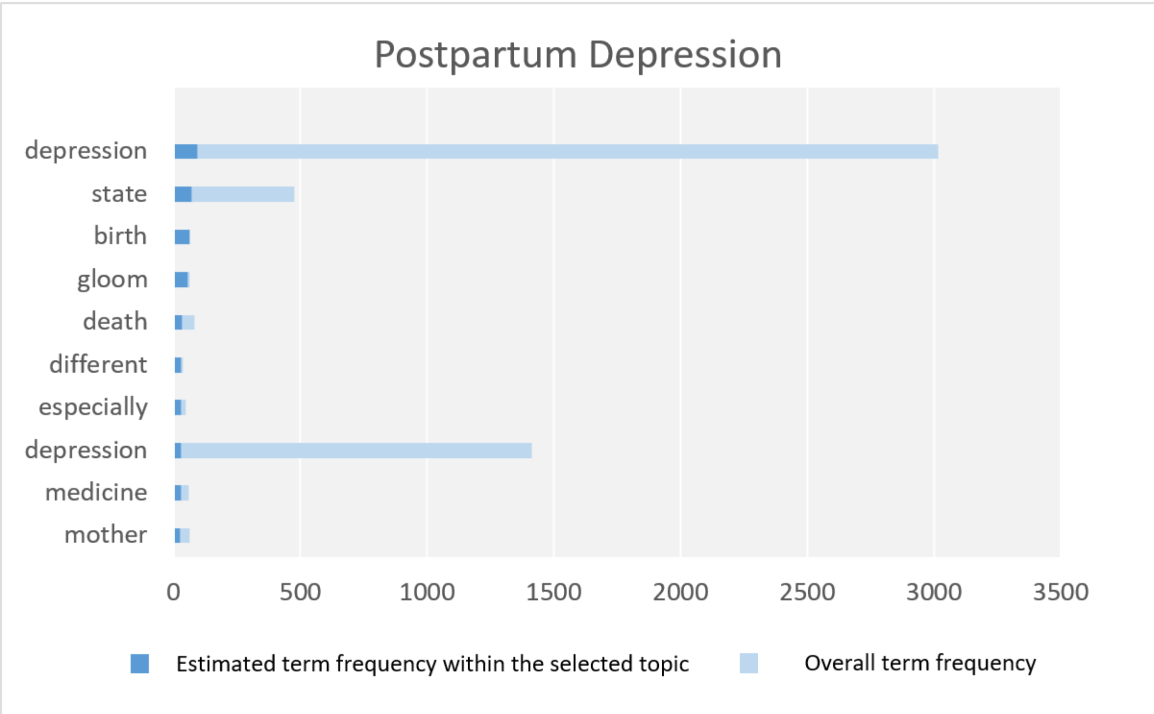

Figure 4. Keyword Frequencies (Macro-Parameter: Diseases & Disorders, Perspective: Drugs & Treatments) See Figure 20 for keywords in Arabic

4.3 Individual Factors

In this section, we discuss the parameters related to the macro-parameter Individual Factors including Anxiety, Sadness, Poor Concentration, Poor Memory, Loss of Appetite, and Fear of Medicine. Figure 5 shows the top 10 key terms for each parameter in Individual Factors macro-parameter.

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 27 February 2023 doi:10.20944/preprints202301.0415.v2

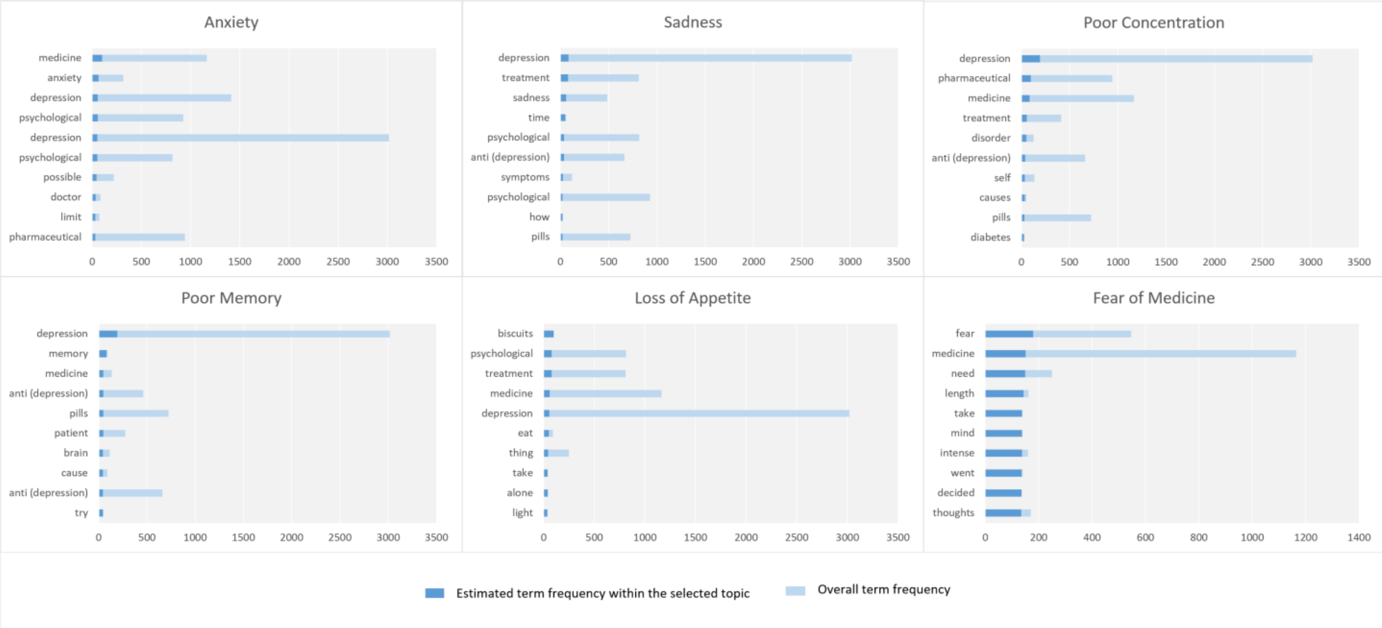

Figure 5. Keyword Frequencies (Macro-Parameter: Individual Factors, Perspective: Drugs & Treatments); See Figure 20 for keywords in Arabic

4.3.1 Anxiety

The parameter relates to anxiety. Among the keywords that our model detected are medicines, anxiety, depression, psychological, depression, psychological, possible, doctor, limit, medicines, blessing, obsessive-compulsive disorder, sleep, pain, treatment, great, health, book, and dose.

4.3.2 Sadness

The parameter relates to sadness. It includes the following keywords depression, treatment, sadness, time, psychological, anti (depression), symptoms, psychological, pills, treatment, deep, disappointed, hopes, wound, and heal. Many tweets in this parameter initiate sadness thoughts. Some of the tweets are poems. We found several tweets that contain poems focusing on sadness due to love. They initiate sadness thoughts in people, although people may enjoy it first, but it can lead to sever depression and suicide like any other intoxication. As it is well known that sad songs may give enjoyment to lovers, but they may also become a source of depression.

4.3.3 Poor Concentration

The Poor Concentration parameter is regarding the difficulties in concentration and the issues related to it. This parameter contains the following keywords depression, medication, treatment, disorder, anti (depression), self, causes, pills, diabetes, deficiency, anxiety, prescription, treatment, psychological, and dangerous. Although these keywords are not directly mentioning concentration, but they are about diseases related to concentration. Most of tweets are about causes of poor concentration including depression and anxiety. For example, the following tweet discusses some of the reasons of poor concentration. *"The reasons for not being able to concentrate: anxiety or depression, both of which are usually caused by the inner reaction of the soul to events that the individual does not accept; sleep disturbance, unfortunately, is prevalent among many young people and affects productivity; some medicine; hormonal imbalance in women after menopause; vitamin b12 deficiency; diabetes disorder."*

4.3.4 Poor Memory

The Poor Memory parameter discusses the negative effects of depression on memory and focus. The parameter is characterized by keywords such as depression, memory, medicine, anti (depression), pills, patient, brain, cause, anti (depression), weakness, concentration, important, dangerous, unknowingly, and effects. People and experts discussed how depression affects memory and one's ability to concentrate and remember. Moreover, some tweets have highlighted that some people fear to use antidepressant because they think that it will cause issues with memory and concentration, below are two example tweets. *“Depression causes poor memory, affects thinking abilities, and causes a reduction in the size of the gray cortex in the brain. Depression is dangerous virus that affects the brain, and its effects are incalculable, and treatment is important. The strange thing is that the patient often refuses antidepressant medication because he believes that it will lead to problems with concentration or memory, etc.”. "Many people need to take antidepressants and anti-anxiety medications... but they are not convinced of them, or they refuse them out of fear using antidepressants, despite their effectiveness, feasibility, and safety in the long run".*

4.3.5 Loss of Appetite

This parameter is about loss of appetite which can happen because of depression. Some of the keywords in this parameter are biscuits, psychological, treatment, medication, depression, eating, taking, alone, light, coffee, chocolate, and food. Some people have mentioned negative effects of antidepressants. For example, the following tweet. *"The withdrawal symptoms of antidepressants are worse than the depression itself… I suffer from insomnia, anxiety, headache, severe dizziness with electricity in the head, panic attacks, difficulty concentrating, dispersion, intense crying for no reason, and loss of appetite…"*

4.3.6 Fear of Medicine

The parameter is regarding fear of medicine. The parameter is represented by keywords such as fear, medicine, need, length, take, mind, intense, thoughts, feelings, wellness, and others.

4.4 Social & Economic Factors

Here, we cover the parameters related to the macro-parameter Social & Economic Factors including Poverty, Unemployment & Insufficient Finances, High Cost of Healthcare, Loss of Loved Ones, Forensic Psychiatry and Social Depression. Figure 6 shows the top ten key terms in each parameter.

4.4.1 Poverty

The parameter relates to poverty as an economic factor that can cause mental health issues. This parameter includes the following keywords sadness, receive, pain, quantity, children, tears, pension, stolen, waiting, bear, medicines, diseases, depression, psychological, fear, etc.

4.4.2 Unemployment & Insufficient Finances

The parameter discusses inadequate finances & unemployment as social and economic factors for depression and mental health issues. The parameter is characterized by keywords such as depression, pills, good, unfortunately, work, difficult, peace, condition, help, tired, tried, mercy, blessings, prison, sons and daughters, suicide, bring, have, and seeker.

Here is an example tweet. *“I have a difficult state of depression. More than once I tried to commit suicide. I am looking for work and I have children that I cannot feed. I have been to prison multiple times. I am tired of going to prison”.*

4.4.3 High Cost of Healthcare

The parameter relates to high cost of healthcare as one of the socioeconomic causes of depression. The parameter is represented by keywords such as mother, depression,

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 27 February 2023 doi:10.20944/preprints202301.0415.v2

thinking, swear, great, please, keep, diabetes, pay, pay her medication, incapacitated, income, sick, tightness, elderly widow, hypertension, and bill.

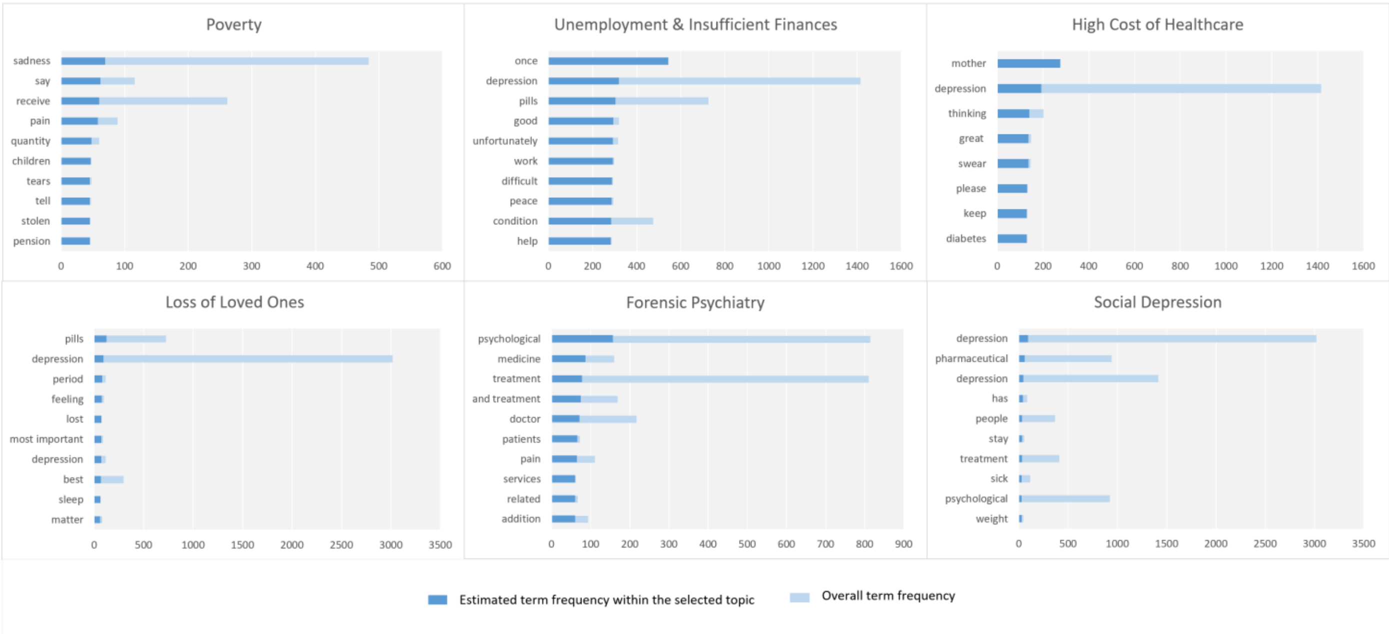

Figure 6. Keyword Frequencies (Macro-Parameter: Social & Economic Factors, Perspective: Drugs & Treatments); See Figure 20 for keywords in Arabic

4.4.4 Loss of Loved Ones

This parameter highlights one of the social causes of depression which is the loss of loved ones. The parameter is represented by keywords such as pills, depression, period, feeling, lost, most important, depression, best, sleep, matter, medicine, even, life, living, death, friend, desire, and Iniesta. Some tweets related to the depression experience of the football player Iniesta, who got depressed from the death of his close friend. The following tweet is an example. *"When I was fighting depression, my best time was when I swallowed pills and went to sleep. Even hugging my wife was like hugging a pillow, without feeling."*

4.4.5 Forensic Psychiatry

The parameter is about forensic psychiatry. It includes the following keywords psychological, medicine, treatment, treatment, doctor, patients, pain, services, related, addition, knowledge, provision, efficiency, facilitation, medication, interaction, pertaining, trial, including, and specifically.

4.4.6 Social Depression

This parameter is about social depression. The parameter is characterized by keywords such as depression, medication, depression, people, stay, treatment, sick, psychological, treatment, anti (depression), bigger, life, city, increase, stress. The parameter emphasizes the fact that society is living in a time when cost of living and healthcare has increased, high achievement become a necessity which led to social depression and anxiety.

4.5 Treatment Options

The parameters associated with Treatment Options macro-parameter are discussed in this section. Figure 7 depicts the ten top key terms based on term frequency.

4.5.1 Walking

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 27 February 2023 doi:10.20944/preprints202301.0415.v2

The parameter discusses walking as treatment for psychological diseases. It is represented by keywords such as prescribe, body, walking, negativity, psychological, energy, nature, anxiety, needs, medications, diseases, fear, equivalent, work, painkillers, emptying, endorphins, sedatives, and reduce. The tweets in this parameter discuss a range of benefits of walking such as triggering the body's whole muscular system and reducing relapses of mental illnesses. For example, the following tweet. *"Why does the body need to walk? walking works to unload negative energy; it is equivalent to some soothing medicines; moves and activates all muscles of the body; endorphins are released as a natural painkiller; reduces relapses of mental illness"*.

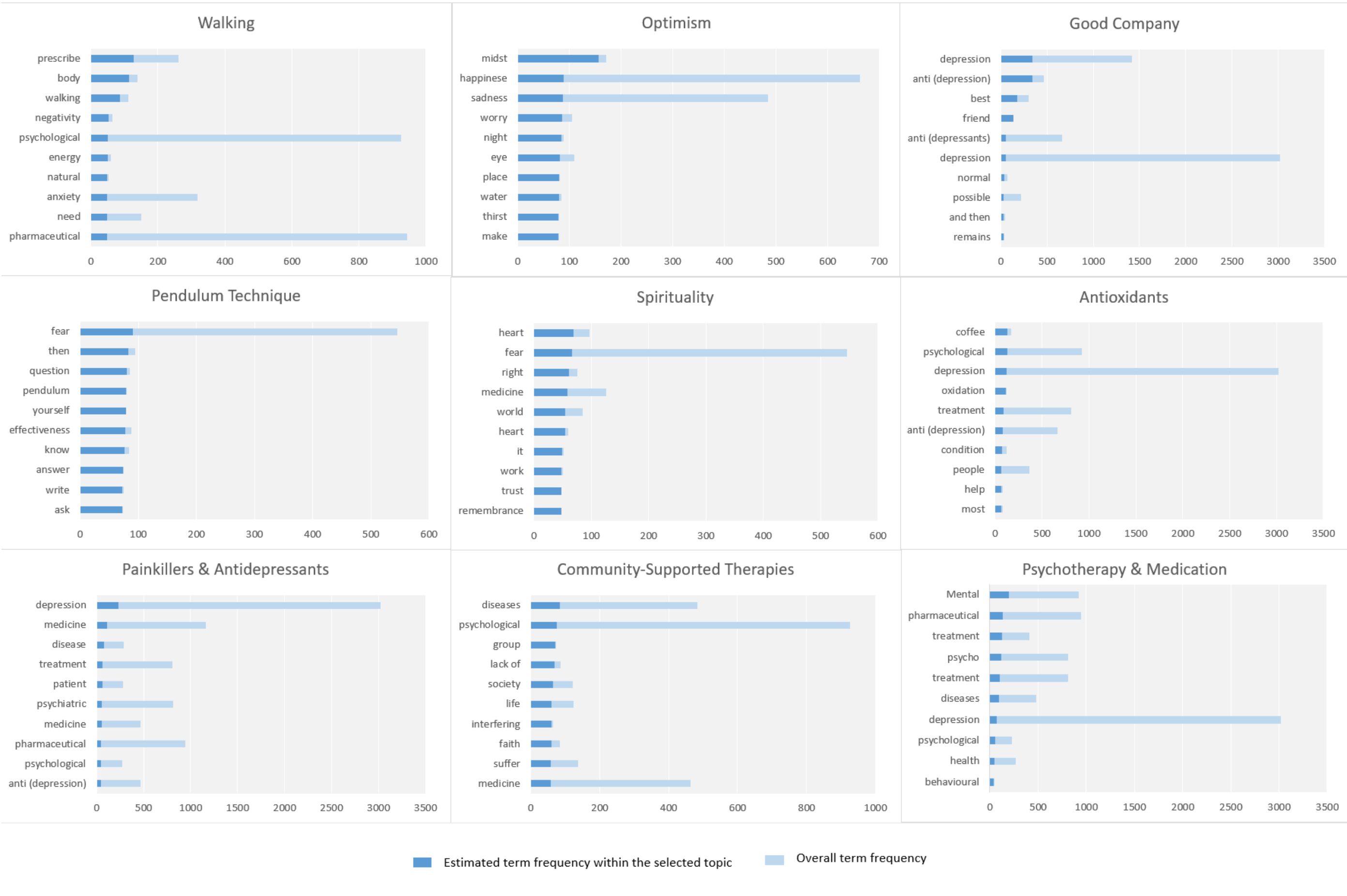

Figure 7. Keyword Frequencies (Macro-Parameter: Treatment Options, Perspective: Drugs & Treatments); See Figure 20 for keywords in Arabic

4.5.2 Optimism

This parameter is regarding Optimism. The parameter is represented by keywords such as midst, happiness, sadness, worry, night, eye, place, water, thirst, make, cross, thunder, blackness, bridge, darkness, sight, make, grow, chagrin, and whiteness.

4.5.3 Good Company

This parameter is about good company and the importance of good friends for mental health issues. Some of the keywords for the parameter are depression, anti (depression), best, friend, anti (depressants), normal, good, defect. People discussed how good friend can be as an antidepressant for depression. There are many tweets in this parameter such as the following, *"Best antidepressant: (a good) Friend"*.

4.5.4 Pendulum Technique

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 27 February 2023 doi:10.20944/preprints202301.0415.v2

This parameter focuses on Pendulum technique. It contains the following keywords fear, then, question, Pendulum, yourself, effectiveness, know, answer, write, ask, feelings, attachment, ready, mention, answer, sharp, intention, depression, anti (depressants), and sun. It was detected as a treatment for psychological issues.

4.5.5 Spirituality

This parameter covers spirituality as treatment for sadness and depression. This parameter includes the following keywords depression, happiness, world, anti (depressants), sedatives, dawn, prayer, loneliness, superiority, firmness, forgetfulness, darkness, witnesses, Glory be to God, medicine, and disease. People discussed how spirituality is used to treat people from sadness and depression. For example, doing good actions, remembering God, praying morning prayer. For example, the following tweets. *"The believing heart replete with the remembrance of God, and trusting in him is not afflicted by boredom, fear, or anguish in this world". "Getting up early morning and pray (Fajr prayer) is better than all sedatives and antidepressants ...".*

4.5.6 Antioxidants

The Antioxidants parameter focuses on the role of antioxidants in fighting depression and mental illnesses. It is represented by key terms such as coffee, psychological, depression, oxidation, treatment, anti (depression), condition, people, helps, most, moods, relieve, improve, anti (oxidants), richness, fruits, combined, plus, and vegetables. The tweets in this parameter have discussed natural sources of antioxidants. The following is an example tweet. *"The spices are used as a natural remedy for depression, Saffron is packed with antioxidant compounds and the carotenoids and carotenoids such as crocin; crocin increases levels of the mood-enhancing neurotransmitter serotonin in the brain."*

Moreover, many tweets have mentioned how coffee is rich in antioxidants and how it can help relieve depression and improve mood state.

4.5.7 Painkillers & Antidepressants

The Painkillers & Antidepressants parameter highlights the difference between the painkillers & antidepressants in terms of the use. The parameter contains the following keywords depression, medications, disease, treatment, patient, psychiatric, medication, psychological, anti (depression), instead of, doctor, depression, for a patient, Cipralex, painkiller, body, give, Celebrex, and hurt. Some tweets have mentioned that antidepressant can be prescribed for physical illnesses. It is not clear from tweets why antidepressant is prescribed. Doctors may see some symptoms of depression.

4.5.8 Community-Supported Therapies

This parameter is about community-supported therapies. this parameter includes the following keywords diseases, psychological, group, lack of, society, life, interfering, faith, suffering, medicine, stigma, factors, deficiency, hereditary, healthy, therefore, requires, support, and sport. Here is an example of a related tweet. *"Psychological diseases involve a set of genetic, familial and social factors, and therefore recovery from them also requires a combination of all these factors, such as regular use of medication, adherence to healthy habits and lifestyle "sports", family support, community awareness and embrace and not to reject those who suffer from it, or to stigmatize them as weak or lacking in faith!"*

4.5.9 Psychotherapy & Medication

This parameter is about the types of medical treatments for psychological illnesses which are the Cogitative Behavioral Therapy (CBT) and the use of medications/drugs. The parameter is characterized by keywords such as psychiatric, medication, treatment, diseases, depression, psychological, health, behavioral, drugs, doctor, medicinal, illness, and pharmaceutical.

A number of tweets discuss psychotherapy and medication. The following tweet stated that *"Mental illness is like physical disease, and it may be stronger and require treatment, whether cognitive-behavioral therapy or drug therapy. I see that in society, they underestimate*

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 27 February 2023 doi:10.20944/preprints202301.0415.v2

mental illness. And I wish this view would change because it prevents the patient from treating himself for fear of people." Another tweet mentioned that *"The conclusion for doctors was, and I publish it here for the benefit of the public: I. Not all cases of depression are treated with medication. Psychotherapy, especially cognitive behavioral therapy, is an effective treatment and should be used before resorting to medication. II. If the patient does not respond to psychological treatment or the severity of the depressive disorder, antidepressants are used."* Additionally, another tweet stated that *"In mental illness, each case is different from the other. And depends on the condition and depression degrees. Medicines are used in severe cases and behavioral therapy benefits most people. Therefore, first, you must visit a doctor, who will examine you and let you know whether you need to take medicine or undergo behavioral therapy."*

Some tweets discussed the types of treatments. For instance, *"post-traumatic stress disorder patients receive several types of treatment: I. Cognitive behavioral therapy: It helps to remove the impact of trauma and reduce its symptoms. II. Support groups: It helps to understand the symptoms more clearly, motivates the patient for treatment, and reduces feelings of loneliness. III. Medicines: such as antidepressants, which help sleep"*. Moreover, *"Psychotherapy is not psychomediacations. The first is based on conversation and speech, and the second is based on using medicines. Combining them is beneficial and necessary for the patient's recovery…"*

Some tweets highlighted the importance of lifestyle for mental health. For example, *"I was able to take control of my mental health when I changed my perspective from the old definition of mental illness, which was limited to taking medicine, to the new concept of mental health, which encompasses all aspects of your lifestyle to maintain your mental health, and this does not diminish the role of medicine, which is sometimes necessary and determined by the specialist doctor"*.

4.6 Treatment Limitations

The parameters related to the macro-parameter Treatment Limitations are covered in this section. Figure 8 shows the top 10 key terms, in each parameter, based on term frequency.

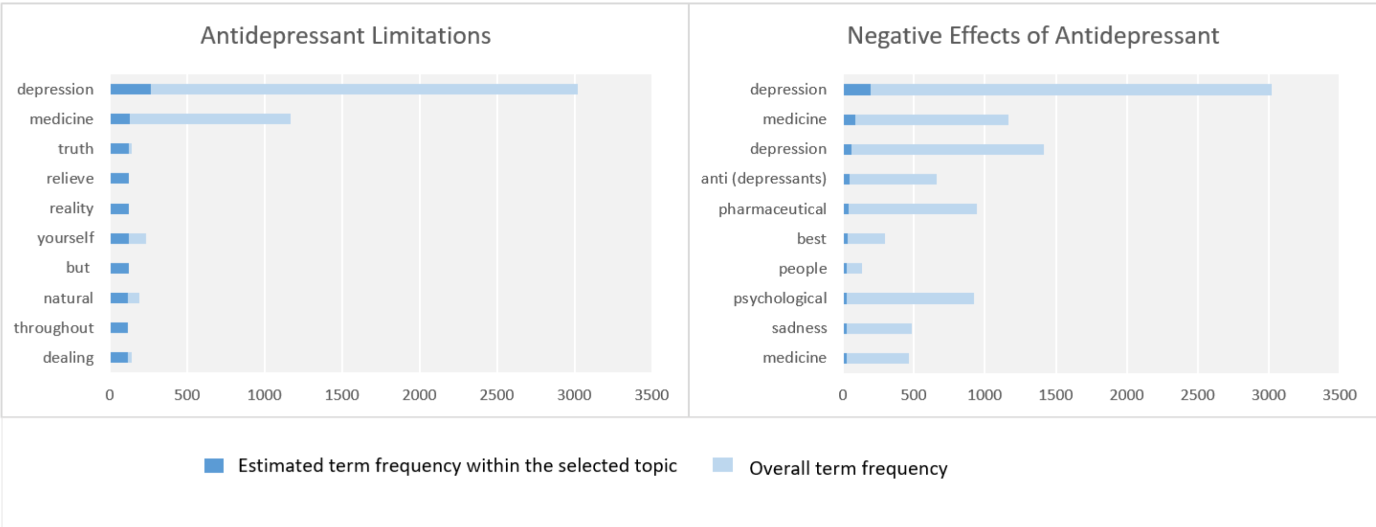

Figure 8. Keyword Frequencies (Macro-Parameter: Treatment Limitations, Perspective: Drugs & Treatments); See Figure 20 for keywords in Arabic

4.6.1 Antidepressant Limitations

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 27 February 2023 doi:10.20944/preprints202301.0415.v2

The parameter discusses antidepressant limitations. It is represented by keywords including depression, medicine, truth, relieve, reality, natural, dealing, mind, crises, right, exaggerating, delight, emotion, happiness, nervousness, etc.

4.6.2 Negative Effects of Antidepressants

The parameter is about the negative effects of antidepressants. It is represented by keywords such as depression, medicine, anti (depressants), people, psychological, sadness, possible, pill, condition, psychological, actually, disease, nervousness, causes, etc. There are many tweets mentioned about the side effects of anti-depressants. As previously noted, we have translated the Arabic content (words and tweets) contextually and made adjustments to the original text, including changes to the information order and the removal of unnecessary or redundant information. We have also omitted parts of the original text that were not useful. Here is an example tweet, *"If the psychiatrist is incompetent, he will give the patient pills that ruin a person's life"*. A tweeter stated that one of her siblings committed suicide after a doctor convinced him that his depression doesn't have a solution and there is no treatment for it. Also, in another case, it was reported in a tweet that someone's close relative was prescribed so many strong pills that if he forgot to take them for a day or two, he would have a bout of screaming and crying.

A number of tweets mentioned some diseases that were detected by our tool as side effects of antidepressant such as obesity, drowsiness, bruxism, and attention-deficit/hyperactivity disorder (ADHD).

Some tweets have discussed the positive sides of using antidepressants. For example, the following tweets. *"… some mental illnesses are chronic like some physical illnesses such as diabetes and high blood pressure. Therefore, you may need to take antidepressants for long periods or all of your life"*.

Several tweets have mentioned other ways for treating depression such as Electroconvulsive therapy (ECT), St. John's wort, and magnesium. Some examples can be found in the following tweets. *"I was treated by Electroconvulsive therapy (ECT), and I got better"*. *"St John's wort is a herbal remedy for depression, but it should not be used by people who take antidepressants or who use heart pills. Also, it should not be used for more than three months"*. *"From the first pill, you can notice the difference, as if you are returning to life. This magnesium is magic for the psyche and for sleep. It is a luxurious thing for those who suffer from increased anxiety, intermittent sleep, very light sleep, insomnia, or those who have obsessions that do not end"*.

4.7 Parameter-Drug Associations (Drugs & Treatments)

In this section, we provide the associations between the detected parameters and drugs for the Drugs & Treatments perspective. These are shown in Table 4 (Column 3) and Figure 9. For example, for the Sadness parameter, the associated drugs include Prozac, Cipralex, Remeron, and Bupropion. These are antidepressants and their association with the Sadness parameter shows that sadness, which is related to depression, may have led to the use of these drugs. The parameters and macro-parameters listed in Table 4 are the same that were listed in Table 3 and discussed earlier in this section (Section 4). Similar to Figure 2, in Figure 9, the first-level branches show the macro-parameters and the second-level branches show the detected parameters. The drugs associated with each parameter, where available, are shown on the third-level branches.

These parameter-drug associations can be discovered automatically as follows. We built a vocabulary of all medicines used for the treatment of psychological illnesses. We searched for these medicines against tweets in each parameter and recorded the associations with the drugs found through the search for each parameter.

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 27 February 2023 doi:10.20944/preprints202301.0415.v2

Table 4. Parameter-Drug Associations (Perspective: Drugs & Treatments)

Macro-Parameter	Parameter	Drugs Associated
Diseases & Disorders	Postpartum depression	No Drugs
Individual Factors	Anxiety	Panadol, Panadol Night, Benzodiazepine, Valium, Xanax
	Sadness	Prozac, Cipralex, Dextromethorphan, Bupropion, Lyrica, Remeron
	Poor Concentration	Omeprazole, Parkizol, Valium, Diazepam, Zolam, Gerfex
	Poor Memory	Saffron, Vitamin D
	Loss of Appetite	Cipralex
	Fear of Medicine	No Drugs
Social & Economic Factors	Poverty	No Drugs
	Unemployment & Insufficient Finances	No Drugs
	High Cost of Healthcare	Faverin, Rofenac, Seroxat
	Loss of Loved Ones	Melatonin, Cipralex, Panadol
	Forensic Psychiatry	No Drugs
	Social Depression	Cipralex, Wellbutrin, Letrozole, Cabergoline, Imipramine, Panadol, Panadol Night, Melatonin
Treatment Options	Walking	Ashwagandha
	Optimism	No Drugs
	Good Company	Panadol Night, Panadol Extra
	Pendulum Technique	No Drugs
	Spirituality	No Drugs
	Antioxidants	Ashwagandha, Vitamin D, Bupropion, Wellbutrin xl, Alprazolam, Midazolam, Valium
	Painkillers & Antidepressants	Celebrex, Cipralex, Prozac, Faverin, Lyrica, Xanax, Morphine
	Community-Supported Therapies	Paroxetine
	Psychotherapy & Medication	Tramadol, Cialis, Prozac, Panadol, Serotonin, Duloxetine, Bupropion, Natural sources of serotonin, Ginkgo
Treatment Limitations	Antidepressant Limitations	Clonazepam, Lorazepam, Diazepam, Amitriptyline, Nortriptyline, Fluoxetine, Sertraline, Paroxetine, Escitalopram, Celebrex, Remeron
	Negative Effects of Antidepressant	Seroxat, Prozac, Vexal, Celebrex, Xanax, Valium, Lyrica, Paroxetine, Fluoxetine, Sertraline, Serotonin, Panadol

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 27 February 2023 doi:10.20944/preprints202301.0415.v2

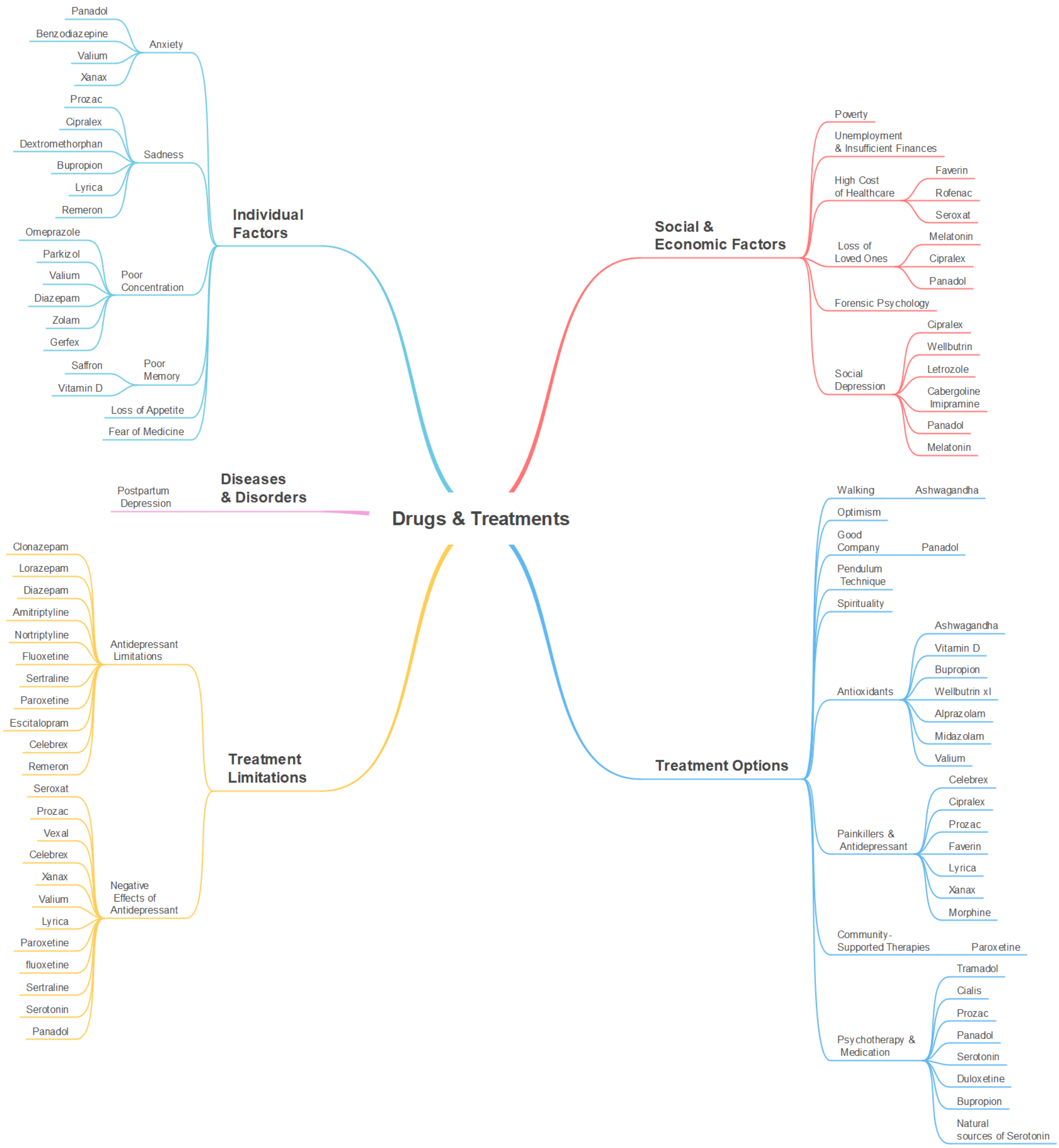

Figure 9. Parameter-Drug Associations Maps (Perspective: Drugs & Treatments)

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 27 February 2023 doi:10.20944/preprints202301.0415.v2

5. Parameter Discovery for Psychological Heath (Causes & Effects)

This section discusses the parameters discovered for the Causes & Effects perspective. An overview of parameters and macro-parameters is provided in Section 5.1. The parameters are explained in Sections 5.2–5.5. Section 5.6 presents the associations between the detected parameters and drugs.

5.1 Overview and Taxonomy

In this section, we focus on Causes & Effects. We created a list of keywords to build a subset of the dataset and identify the parameters for Causes & Effects perspective. Table 5 provides a list of keywords used. The dataset that we got after filtering data contains 88,566 tweets.

Table 5. Keywords Used to Discover Parameters (Perspective: Causes & Effects)

Keywords Used to Discover Parameters for Causes & Effects Perspective
جانبيه، جانبية، اثار، آثار، بسبب، سببه، تسبب، يسبب، يسببه، يسويه، يسوية، جاب
side, effects, effects, because of, cause it, it causes, it causes, causes it, caused by, cause, brought
نتيجة، نتيجة، نتيجه، وزن، وزني، كوليسترول، اضطرابات، خمول، شقيقه، شقيقة
result, result, result, weight, my weight, cholesterol, disorders, lethargy, Migraine, Migraine
شهيه، شهية، أيض، ايض، ذاكرة، ذاكره، تركيز، دوخة، دوخه
appetite, appetite, metabolism, metabolism, memory, memory, concentration, dizziness, dizziness,
نوم، ارق، أرق، صداع، بكاء، معدة، معده، فرط الحركة، فرط الحركه، نقص الانتباه
sleep, insomnia, insomnia, headache, crying, stomach, stomach, hyperactivity, hyperactivity, attention deficit
إكتئاب، اكتئاب، كابه، كابة، كآبة، كآبه، إدمان، ادمان
depression, depression, depression, depression, depression, depression, addiction, addiction

An overview of the parameters of the Causes & Effects perspective is provided in Table 6. The macro-parameters are listed in column 1. Four macro-parameters are included: Diseases & Disorders, Individual Factors, Social and Economic Factors, and Treatment Options. In the second column, twenty-two parameters are listed. There are some parameters that are related to one another and have been merged. The third column contains the IDs of the parameters. Column 4 displays the keywords' percentages of parameters. In the fifth column, the top 20 keywords related to each parameter are listed. In order to facilitate the comprehension of Arabic contents by English readers, the keywords as well as other contents such as the tweets were contextually translated.

Using the parameters our software detected, a taxonomy (see Figure 10) reflecting the Causes & Effects perspective was developed. The taxonomy displays the parameters along with their macro-parameters. The first level is represented by the macro-parameters Diseases & Disorders, Individual Factors, Social & Economic Factors, and Treatment Options. The detected parameters are displayed on the second level of branches.

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 27 February 2023 doi:10.20944/preprints202301.0415.v2

Table 6. Macro-Parameters and Parameters (Perspective: Causes & Effects)

Macro-Parameter	Parameter	ID	(%)	Keywords
Diseases & Disorders	Attachment Disorder	8	3.8	النفسه، ممكن، الصحه، اهل، تعش، حياتك، مستشفى، شخص، قصه، اغنيه، واقع، وعافيه، ونجاح، انحبست، وخسرت، التعلق، وجمهور، وفلوس، غنتها psychological, possible, health, family, live, your life, hospital, person, story, song, reality, well-being, success, locked up, lost, attachment, audience, money, sung by her
	Insomnia	12 24	3.2 2.5	النوم، الحزن، يارب، قلق، لطبيب، عيني، اخاف، اكتئاب، اعراض، مني، اكون، الخوف، اسمي، شتات، نفسي، وحين، علمني، النعم، امري sleep, sadness, Lord, anxiety, doctor, eye, fear, depression, symptoms, from me, I am, fear, name, diaspora, myself, when, teach, blessings, matter
	Obsessive Compulsive Disorder (OCD)	30	2.2	افتقد، لذه، النوم، شعور، خوف، طريق، يومي، بدل، الراحه، التركيز، حياتي، كابه، التفكير، عاده، الهدوء، الاكتئاب، ذاتي، مراجعه، الذهني، ممارسه miss, pleasure, sleep, feeling, fear, way, daily, instead, comfort, concentration, my life, depression, thinking, habit, calm, depression, self, review, mental, practice
	Post-Surgery Depression	23	2.6	العمليه، الاكتئاب، الشعور، اكل، الشخص، معين، تاثير، سلبي، دايما، وقت، المعده، ياكل، الطبي، بيحصل، الغذائي، الدعم، بالوحده، بيك، باكل، يخرج operation, depression, feeling, eating, person, specific, effect, negative, always, time, stomach, eat, medical, happen, food, support, loneliness, for you, eat, get out
	Chronic physiological Diseases	9	3.7	الاكتئاب، اكتئاب، تسبب، النفسه، مريض، مزمن، الملك، الطبيه، المخ، خوف، الامراض، سلمان، معاناه، جراحي، يسبب، بمدينه، علاقه، نفسه، والاعصاب، تعوض depression, depression, cause, psychological, sick, chronic, king, medical, brain, fear, diseases, Salman, suffering, surgical, cause, city, relationship, psychological, nerves, compensate
Individual Factors	Fear	16	2.9	اترك، واهتم، خوف، زياده، الوزن، عنك، الموضوع، بالنوم، امراض، الفقر، ابعد، فكر، وكذا، فرق، الخوف، طبيب، الصحه، الوجه، خوفك، مصادر leave, care, fear, increase, weight, about you, subject, sleep, diseases, poverty, keep away, think, and so on, difference, fear, doctor, health, face, your fear, sources
	Sadness	19	2.9	العالم، اقدر، اكتئاب، نفسي، حقيقي، للناس، اكمل، مني، طبيعي، عمري، احاول، حاجه، حاجات، بعمل، خوف، شخص، واني، سنين، وقت، ابقى world, I can, depression, wish, real, people, complete, me, normal, age, try, need, needs, work, fear, person, I, years, time, stay
	Loneliness	4	4.6	اتمنى، قلبي، لوحده، الحزن، تمام، تمر، الوحده، عقلي، المرحله، الخوف، والتركيز، ليالي، الانسان، والتفكير، والقلق، المجهول، التفاصيل، يعوضني، الثقه، يهدا wish, heart, alone, sadness, ok, pass, loneliness, mind, stage, fear, focus, nights, human, thinking, anxiety, unknown, details, compensate, trust, calm down
	Lacking Passion	11 15	3.3 2.9	كابه، عايز، حاجه، نفسي، اكون، اوقات، اللحظه، رغبه، عارمه، اختفي، والعالم، بتجيلي، التواجد، تقال، موجود، حاسس، عايزه، اكتئاب، الحزن، المنظر depression, want, need, myself, be, times, moment, desire, overwhelming, disappear, the world, have, presence, heavy, exist, feel, want, depression, sadness, view
	Suppressing Emotions	17	2.9	الحزن، حزن، عضوي، سبب، بعدها، قادر، شخصيه، مرض، تجربه، تنام، ممكن، زعلان، حاجه، صدرك، مكنتش، اتمنى، احكي، يقل، جواك، اعيشها sadness, sorrow, physical, cause, after, able, personality, disease, experience, sleep, possible, upset/angry, need, your chest, was not, wish, tell, say, inside, live
	Negative Emotions	21	2.7	اكتئاب، حاله، الناس، ودا، بسببه، الانسان، الحياه، كابه، نفسيه، والبكاء، نوم، الحديث، حياتنا، نفسك، عندنا، الحزن، قلق، دائم، عباره، حب depression, condition, people, this, because, human, life, depression, psychological, crying, sleep, conversation, life, yourself, have, sadness, anxiety, permanent, phrase, love
	Devil (Negative Thoughts)	22	2.7	اهم، الحزن، قلق، دوامه، والخوف، القلب، الشيطان، حياتك، مرتاح، وسوء، احزان، مستقر، سببه، الحاليه، دوم، بالماضي، بيجعلك، متوتره، يدمر، زراعه most important, sadness, anxiety, whirlpool, fear, heart, devil, life, comfortable, bad, sorrows, stable, caused, current, last, past, make, tense, destroy, cultivate
	Lacking Inner Peace	29	2.2	الحياه، السلام، قلق، ارق، ابتعد، فيك، الناس، كثيره، اشياء، موضوع، غضب، بداخلي، التركيز، ربك، صراع، الح، خوف، والقلق، النفسه، الفرح life, peace, anxiety, insomnia, stay away, in you, people, many, things, topic, anger, inside me, focus, your Lord, struggle, fear, anxiety, psychological, joy
Social & Economic Factors	Study	6 7 14	4.2 4 2.9	قلق، مشكله، الموضوع، باذن، خوف، تحدث، النفسي، تؤدي، المدارس، الدراسي، المستوى، التاثير، تاخر، مساحه، الذهاب، قادمه، نخبه، للمدرسه، اعاقه، المستشارين concern, problem, subject, permission, fear, cause, psychological, lead, schools, academic, level, impact, delay, space, going, coming, elite, to school, disability, counsellors
	Work	5	4.5	اكتئاب، الاكتئاب، حد، حاجه، ممكن، الدوام، مكتئب، طول، خوف، جاني، محدش، الحمدلله، حرفيا، لسه، حياه، كفايه، المجتمع، نفسي، بيجيلك، نقص depression, limit, need, possible, permanence, depressed, length, fear, came, no one, praise be to God, literally, still, life, sufficiency, society, psychological, coming, deficiency

	Lifestyles	25	2.5	وقت، اكتئاب، الحزن، سببها، نعمه، الكلام، المشاكل، لتعرف، الصمت، فهمت، بداخلك، تظاهرت، بالغباء، والتزمت، وابتسمت، تجنب، العافيه، وزن، بالنسبه، المستشفى time, depression, sadness, cause, grace, speech, problems, know, silence, understood, inside, pretended, stupid, committed, smiled, answered, wellness, weight, in relation to, hospital
	High Cost of Healthcare	26	2.4	اكتئاب، نفسى، عرفت، اعمل، معندش، الجلسه، الاكتئاب، نفسه، فتره، الخير، للاكتئاب، الفصول، امراض، بعانى، خوف، الصعبه، المنزل، الشارع، الاسره، الحياه depression, myself, knew, make, I don’t have, session, depression, psychological, period, good, for depression, seasons, diseases, suffering, fear, difficult, home, street, family, life
	Seasonal Depression	2 18	5.7 2.9%	اكتئاب، السبت، كابه، الاكتئاب، حاد، فبنى، الولاده، تحس، الشتاء، الجو، برش، فتره، اعرف، شهر، جانى، الناس، سبب، احس، بالجو، داخل depression, Saturday, gloom, depression, severe, I have, birth, feel, winter, weather, spray, period, know, month, offender, people, cause, feel, atmosphere, inside
Treatment Options	Emotional Release (Psychotherapy)	1	6.3	اكتئاب، الحياه، خوف، الشعر، بزيل، قص، الشتا، نوم، اسمه، اهلى، اصحى، شبعت، داخله، جانى، دخلت، ريحه، جابتلى، بجنى، بجيب، الناس depression, life, fear, hair, remove, cut, winter, sleep, name, family, wake up, satiate, inside, side, entered, smell, bring, come, answer, people
Treatment Options	Good Friends	10 13	3.4 3	اكتئاب، افضل، قلق، شخص، تستطيع، اعمق، بجديه، تمزح، بداخلك، بجمع، عفويه، السعى، وصول، استمراريه، رائع، تضمنلك، الامرين، الام، تسبب، ماحصلش depression, better, anxiety, person, can, deeper, seriously, kidding, inside you, collect, spontaneity, quest, reach, continuity, wonderful, include you, the two things, the mother, cause, not happened
Treatment Options	Spirituality	20	2.8	وفاه، واعوذ، نوم، اعوذ، الحزن، النفسيه، النفس، الفرح، القلب، راحه، حياه، الجسد، الروح، المجتمع، قلق، السؤال، ظلم، الاحوال، سواد، كسره death, refuge, sleep, I seek refuge, sadness, psychological, spirit, joy, heart, rest, life, body, soul, society, anxiety, question, injustice, conditions, blackness, break
Treatment Options	Surgery	3	5.6	عمليه، الاكتئاب، الحزن، ساعات، جراحيه، نجاح، بعانى، المستقبل، النوم، والنفسيه، الطبيه، المريض، المزاجيه، سلمان، الطبيعيه، الاولى، والتفكير، والقلق، الزائد، الدائم operation, depression, sadness, hours, surgery, success, suffering, future, sleep, psychological, medical, patient, mood, Salman, natural, first, thinking, anxiety, excess, permanent

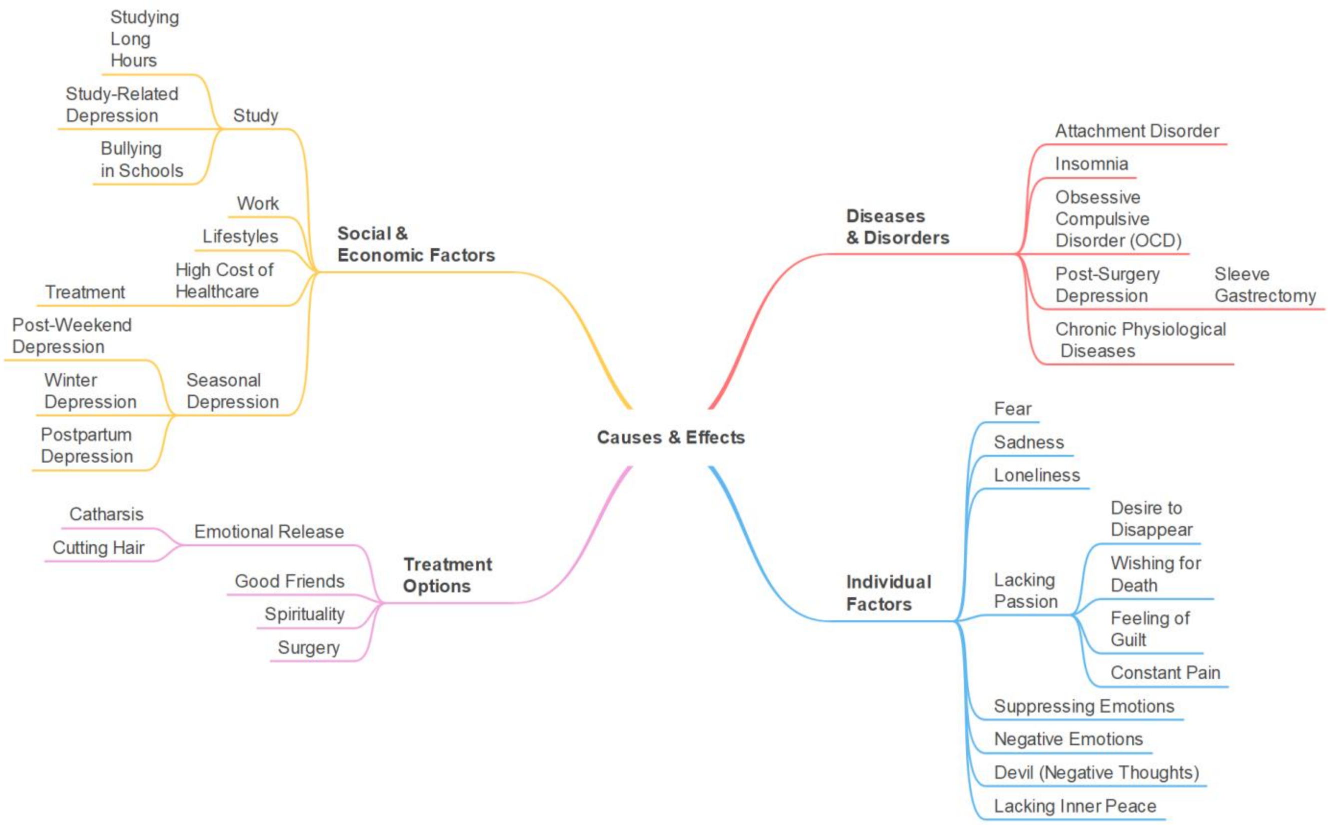

Figure 10. Taxonomy (Perspective: Causes & Effects)

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 27 February 2023 doi:10.20944/preprints202301.0415.v2

5.2 Diseases & Disorders

In this section, the parameters that belong to the macro-parameter Diseases & Disorders are discussed including Attachment Disorder, Insomnia, and Obsessive Compulsive Disorder (OCD). Figure 11 depicts the ten top key terms, in each parameter, according to term frequency (for further details see Section 3.6).

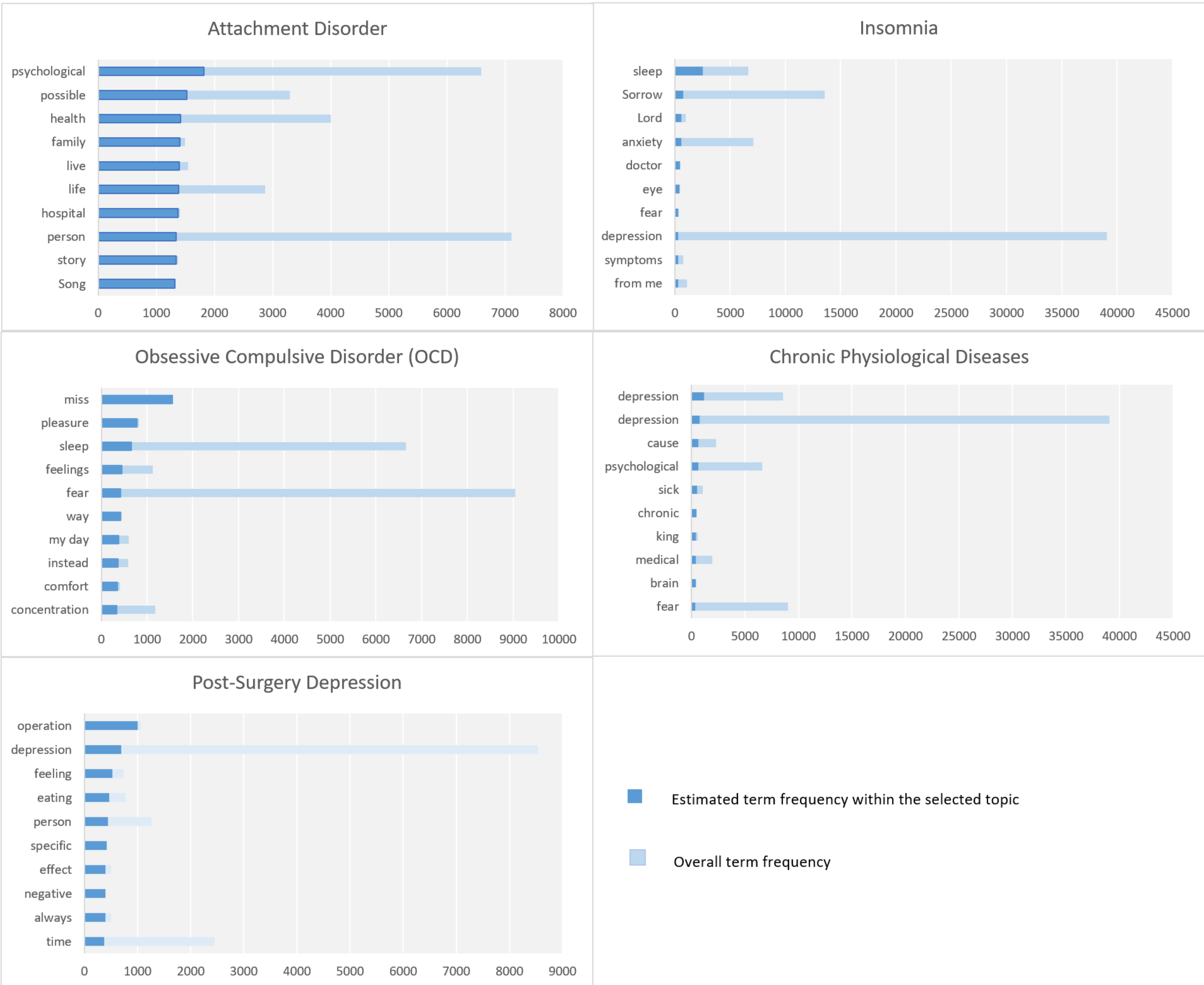

Figure 11. Keyword Frequencies (Macro-Parameter: Diseases & Disorders, Perspective: Causes & Effects); See Figure 21 for keywords in Arabic

5.2.1 Attachment Disorder

This parameter is about attachment disorder which is a form of mental illness or behavioral condition that interferes with a person's capacity to establish and sustain relationships. It relates to the challenges involved in understanding emotions, expressing affection, and placing one's trust in others. The parameter is represented by keywords such

 doi:10.20944/preprints202301.0415.v2

as psychological, health, family, live, your life, hospital, person, reality, well-being, success, locked up, lost, attachment, money, etc. People discussed that someone should avoid excessive attachment to loved ones as it can destroy person's life. Furthermore, a case of celebrity who was deceived by loved one has been discussed.

5.2.2 Insomnia

The parameter focuses on Insomnia which can be a cause or an effect of other psychological issues. The parameter is characterized by keywords such as sleep, sadness, anxiety, doctor, eye, fear, depression, symptoms, fear, diaspora, matter, etc. People discussed different reasons for insomnia such as excessive worry, fear, depression, anxiety about events or people, sadness, excessive thinking, exhaustion, or loss and nostalgia.

5.2.3 Obsessive Compulsive Disorder (OCD)

The parameter is regarding obsessive compulsive disorder (OCD) which is a is a prevalent mental health problem characterized by compulsive behaviors and obsessive thoughts. According to our model, the following keywords were detected: miss, pleasure, sleep, feeling, fear, ways, change, rest, focus, depression, thinking, habit, calm, depression, self, review, mental, and practice. People discussed the symptoms of OCD, the causes and treatment. For example, someone tweeted: *"I miss the feeling of comfort, peace, and reassurance, I miss mental and psychological calmness, I miss the pleasure of sleeping without the trouble of thinking, I miss practicing my life without self-flagellation and without reviewing my mistakes and actions, I miss the pleasure of spending the day without focusing on the smallest details, I miss the pleasure of moving on a path without fear of a tragic end awaiting me."* Here is another tweet. *"Obsessive-compulsive disorder is the control of an idea that its owner knows is absurd, forcing him to repeat actions, such as making sure the door is locked, cleanliness, or purity, to a degree that may affect the productivity of the individual. This indicates underlying anxiety and can be treated with some medication and dialogue..."*

5.2.4 Post-Surgery Depression

This cluster is about post-surgery depression, and it focuses on surgeries as cause of depression. It includes the following keywords operation, depression, feeling, eating, person, specific, effect, negative, always, time, stomach, eat, medical, happen, food, support, loneliness, for you, eat, get out. The tweets associated with this parameter are mostly related to the depression that occurs after Sleeve gastrectomy surgery, but depression can happen as a side effect of any other surgery. People mentioned that depression occurs after the Sleeve gastrectomy operation because the stomach is restricted to a certain food, and this has a negative effect, such as feeling lonely or that the person cannot go out and eat a variety of foods like before.

5.2.5 Chronic Physiological Diseases

The Chronic physiological Diseases parameter discusses various diseases that could lead to depression. The following keywords were detected by our model: depression, depression, cause, psychological, sick, chronic, king, medical, brain, fear, diseases, Salman, suffering, surgical, cause, city, relationship, psychological, nerves, and compensate. When a person suffers from a disease, that affects his ability to move and could lead to some changes in lifestyle, which could result in depression. A tweet mentioned five chronic diseases which cause depression and sadness including diabetes mellitus, arthritis, heart disease, kidney failure, and thyroid gland. Some other tweets linked COVID-19 infection to a range of chronic neuropsychiatric disorders, including depression, memory problems, and Parkinson's disease-like disorders.

5.3 Individual Factors

We highlight here the parameters under the macro-parameter Individual Factors. There are eight parameters. Figure 12 depicts the top 10 keywords, in each parameter, based on term frequency.

5.3.1 Fear

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 27 February 2023 doi:10.20944/preprints202301.0415.v2

This parameter is about fear as cause or effect of psychological illnesses. Our model detected the following keywords: leave, care, fear, weight, gain, about you, subject, sleep, diseases, poverty, keep away, think, difference, fear, doctor, health, face, your fear, and sources. The tweets highlighted different kinds of fear including fear of losing persons, fear of diseases, fear of poverty, and others. Here is an example tweet. "*Take good care of your immunity and leave your fear of viral diseases behind. Focus on good nutrition and leave your fear of gaining weight. Get a good sleep and leave the fear of facial wrinkles. Take care of the multiplicity of your sources of income and Leave the fear of poverty*".

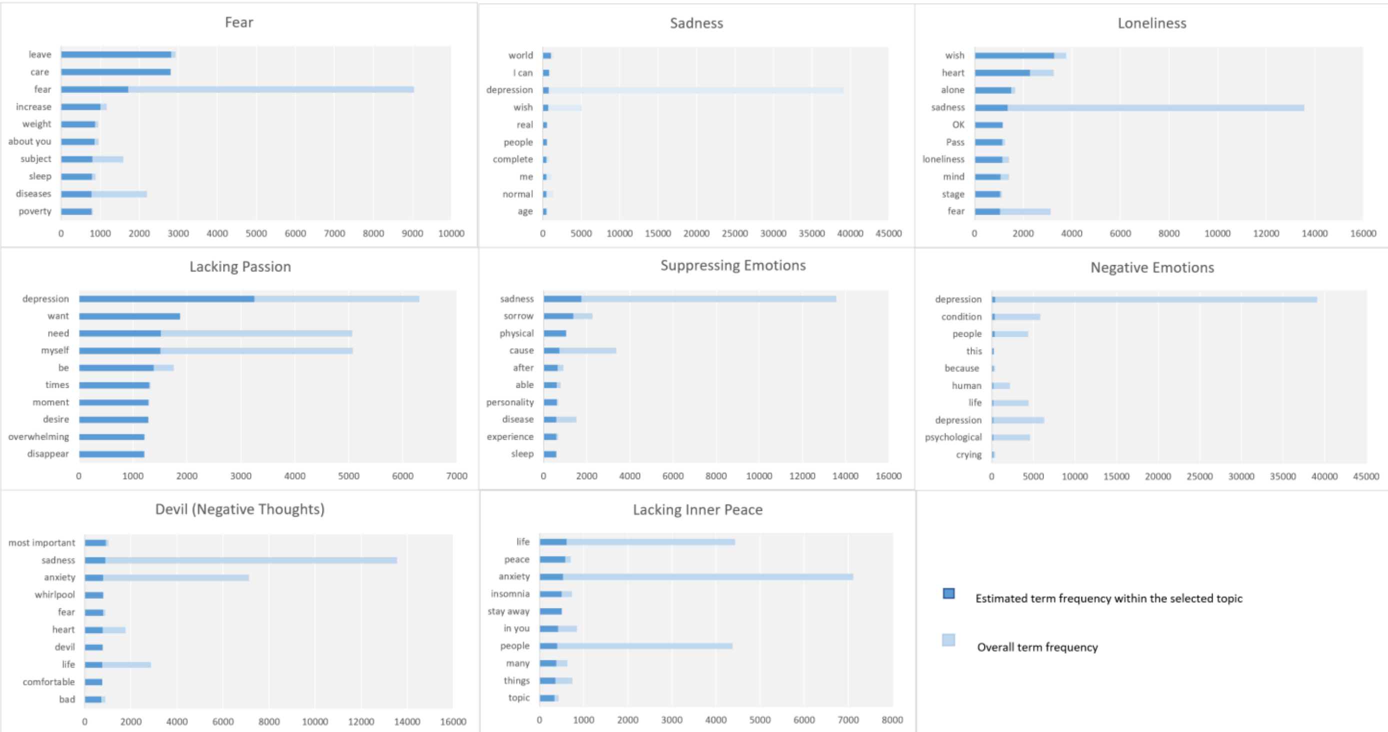

Figure 12. Keyword Frequencies (Macro-Parameter: Individual Factors, Perspective: Causes & Effects); See Figure 21 for keywords in Arabic

5.3.2 Sadness

The parameter is about sadness with could be a symptom, a cause, or an effect of psychological diseases. It is represented by keywords including world, depression, wish, real, people, complete, me, normal, age, try, need, needs, work, fear, person, years, time, stay, etc. This parameter is similar to a parameter covered in the previous perspective. For more details see Section 4.3.2.

5.3.3 Loneliness

This parameter is about loneliness, which is characterized by keywords such as wish, heart, alone, sadness, complete, pass, loneliness, mind, stage, fear, focus, nights, human, thinking, anxiety, unknown, details, compensate, trust, and calm down. Someone tweeted *"I hope that God will compensate me for all the nights of loneliness, sadness and misery, and reassure my heart …"*

5.3.4 Lacking Passion

This parameter is about people who lost sense of value and pleasure in everything, and they wish for death. This parameter includes the following keywords depression, want, need, myself, times, moment, desire, overwhelming, disappear, the world, have, presence, heavy, exist, feel, want, depression, sadness, and view. People discussed different symptoms associated with lacking passion such as feeling of helplessness, low in energy and exhaustion, constant pain, and the feeling of guilt. Other tweets have mentioned

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 27 February 2023 doi:10.20944/preprints202301.0415.v2

other symptoms including lack of self-esteem, self-loathing, lack of focus, loss of hope, and the desire to disappear.

5.3.5 Suppressing Emotions

This parameter is about suppression of emotions either the positive and negative ones which can lead to depression and other psychological illnesses. Based on our model, the following keywords were detected: sadness, sorrow, physical, cause, after, able, personality, disease, experience, sleep, possible, upset/angry, need, your chest, was not, wish, tell, say, inside, and live. Some tweets have highlighted some of the effects of suppressed emotions such as anxiety, depression, and other stress-related illnesses. Other tweets have mentioned the importance of discussion and expressing emotions for psychological health.

5.3.6 Negative Emotions

The Negative Emotions parameter is about people who talks about and share their personal negative experiences and generalize it, so they cause depression for themselves and others in the society. It is represented by keywords such as depression, condition, people, friendliness, because, human, life, depression, psychological, crying, sleep, conversation, life, yourself, have, sadness, anxiety, permanent, phrase, and love.

5.3.7 Devil (Negative Thoughts)

This parameter is regarding the devil and negative thoughts. It is characterized by keywords such as most important, sadness, anxiety, whirlpool, fear, heart, devil, life, comfortable, bad, sorrows, stable, caused, current, last, past, make, tense, and destroy. People discussed how devil negatively affects people's mental health. For example, the following tweet. *"Remember that one of devil's most important goals is to cultivate sadness and fear in the heart, so that he does not make you stable or comfortable, but rather discontented, anxious, and pessimistic. He links you to the past, its pains, and the sorrows it causes you, and links you to the future, its fears and anxieties; To make you always in a tense spiral and mistrust, and his goal is to destroy your current moment and spoil your life."*

5.3.8 Lacking Inner Peace

This parameter is about lacking inner peace. The following keywords were detected by our model: life, peace, anxiety, insomnia, stay away, in you, people, many, things, topic, anger, inside me, focus, your Lord, struggle, urgency, fear, anxiety, psychological, and joy. The parameter focuses on the importance of inner peace for fighting the depression. People discussed different things such as how to get the inner peace by avoid passing judgment on people. Here is an example tweet. *"If you do not feel peace within you, you will find many things in life that cause you anger, chaos, grumbling, anxiety, and conflict. How do I find peace inside me? get closer to your Lord; avoid passing judgment on people; stay away from focusing on any disturbing topic; live life with grace, not with complexity."*

5.4 Social & Economic Factors

There are five parameters under the Social & Economic Factors macro-parameter. Figure 13 shows the ten top 10 keywords, in each parameter, based on term frequency.

5.4.1 Study

This parameter covers various study-related issues which could cause psychological illnesses such as studying for long hours, studies related depression, and bullying in schools. The parameter contains the following keywords concern, problem, subject, permission, fear, cause, psychological, lead, schools, academic, level, impact, delay, space, going, coming, elite, to school, disability, and counsellors. The tweets discussed the causes of psychological illness. For instance, the following tweet highlight different causes of psychological illnesses and some solutions which don't lie in drugs. *"When the psychologist's tweets highlight how some psychological disorders, such as depression, anxiety, etc., develop as a result of people's exposure to psychological trauma, abused childhood, or some social problems*

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 27 February 2023 doi:10.20944/preprints202301.0415.v2

such as divorce and others. It is natural to find that the solution to these problems does not lie in drug treatment"

Furthermore, a tweet stated a list of disorders which are related to certain causes. These disorders include anxiety disorders, especially panic attacks and anxiety about disease, depression and mood disorders, traumatic disorders, personality disorders, dissociative disorders, and internal psychological struggle due to social pressure. Another tweet highlighted various socioeconomic causes of depression and psychiatric disturbances. A tweet reported that *"the poor economic state of the family may cause social problems and bad psychological effects that lead to excessive thinking and eventually lead to mental illnesses"*.

A number of tweets reported that universities and schools cause of fear and depression. Moreover, several tweets discussed the issues bullying in schools and how it affects academic progress of students. For example, a tweet mentioned that bullying in schools can cause depression, anxiety, social shyness, social phobia, and eventually delay in the academic level.

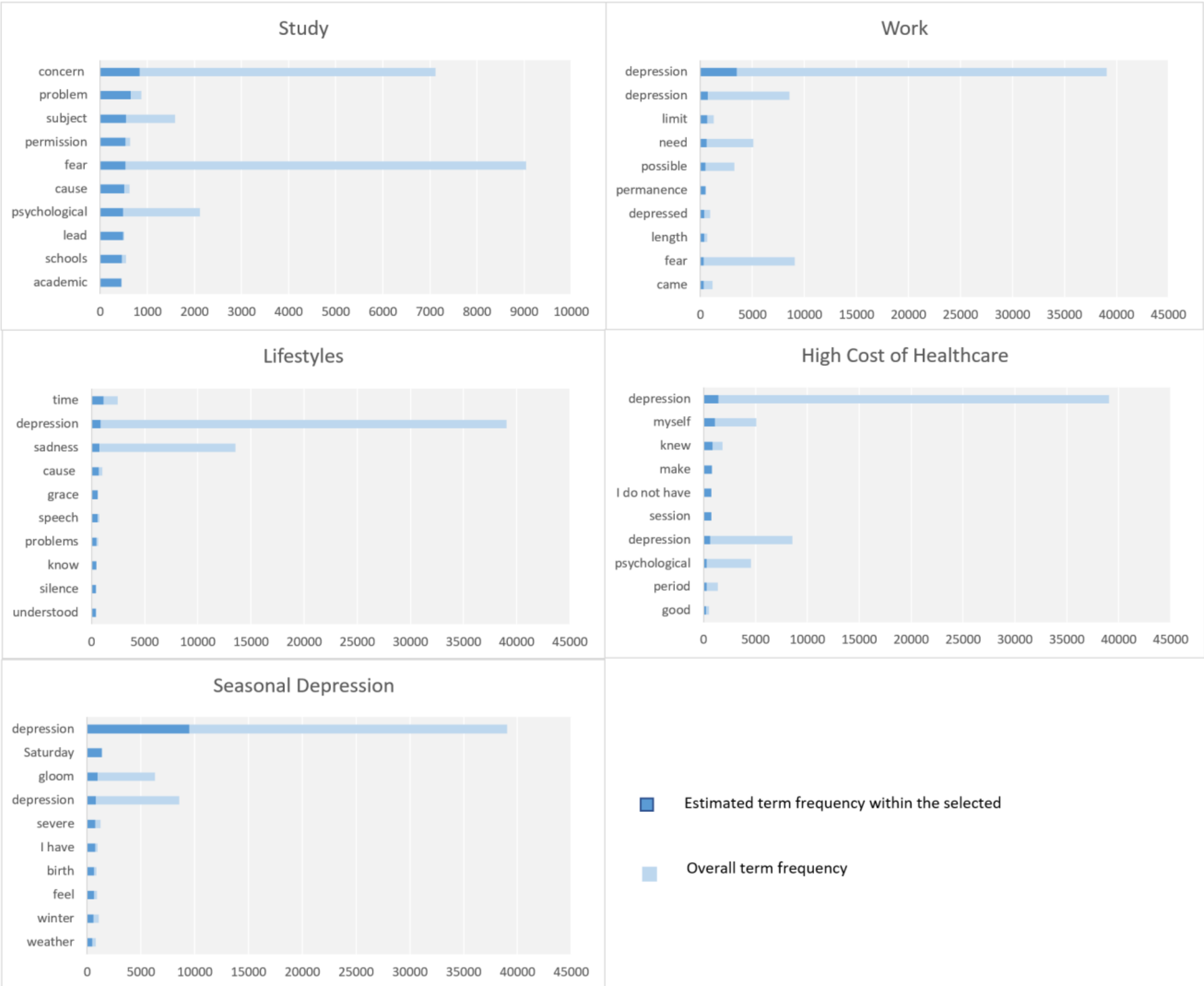

Figure 13. Keyword Frequencies (Macro-Parameter: Social & Economic Factors, Perspective: Causes & Effects); See Figure 21 for keywords in Arabic

5.4.2 Work

This parameter focusses on the work as cause of psychological issues. Among the keywords that our model detected are depression, limit, need, possible, permanence, depressed, length, fear, offender, no one, praise be to God, literally, still, life, sufficiency, society, coming, and deficiency. People discussed how long working hours affect mental

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 27 February 2023 doi:10.20944/preprints202301.0415.v2

health and ow leaving very little time for family and social relationships can result in depression and family breakup.

5.4.3 Lifestyles

This parameter is about the lifestyle as a cause of psychological illness including eating and thinking patterns. The parameter is represented by keywords such as time, depression, sadness, cause, grace, speech, problems, know, silence, understood, inside, pretended, stupid, committed, smiled, answered, wellness, weight, in relation to, hospital. Here are some example tweets of maintain good lifestyle. For example, the following tweet, *"Most people write about pain and talk about fatigue until their minds are programmed to be depressed and think negatively which cause them illnesses"*.

Here is another example tweet. *"Malnutrition is the cause of mental illness, which can be treated with diet, exercise, cupping, and good company rather than medicine. The consumption of indomie, soft drinks, and drinks containing stimulants causes fear. Alcohol, smoking, and sweets cause anxiety and depression."*

5.4.4 High Cost of Healthcare

This parameter is about high cost of healthcare as socioeconomic factor for psychological illnesses. The parameter includes the keywords depression, knew, make, have, session, psychological, period, good, for depression, seasons, diseases, suffering, fear, difficult, home, street, family, and life. This parameter is similar to a parameter covered in the previous dimension. For further details see Section 4.4.3.

5.4.5 Seasonal Depression (Seasonal Effective Disorder)

This parameter is about seasonal depression which is a type of depression which occurs as a result of the change of seasons. The parameter is represented by keywords such as depression, Saturday, gloom, depression, severe, I have, birth, feel, winter, weather, spray, period, know, month, offender, people, cause, feel, atmosphere, and inside. From tweets and keywords, different types of depression have been mentioned such as post-weekend depression, postpartum depression, and winter depression.

5.5 Treatment Options

Figure 14 displays the most frequent keywords in each parameter in Treatment Options macro-parameter.

5.5.1 Emotional Release (Psychotherapy)

The parameter is regarding emotional release (catharsis) as part of Psychotherapy. The following keywords were detected by our model: depression, life, fear, hair, remove, cut, winter, sleep, name, family, wake up, satiate, inside, side, entered, smell, bring, come, answer, and people. Many tweets have talked about cutting hair as a way of emotional release. For example, The following tweet. *"Cutting hair removes 100% of life's depression"*

5.5.2 Good Friends

This parameter is about good friends, and it is described by the following keywords depression, better, anxiety, person, can, deeper, seriously, kidding, inside you, collect, spontaneity, quest, reach, continuity, wonderful, include you, the two things, the mother, cause, not happened. People discussed the importance of good friends for psychological health. Here is an example tweet. *"When you talk to good friend while you are in a state of anxiety and fear, you become reassured because of his deep words and great actions"*.

 doi:10.20944/preprints202301.0415.v2

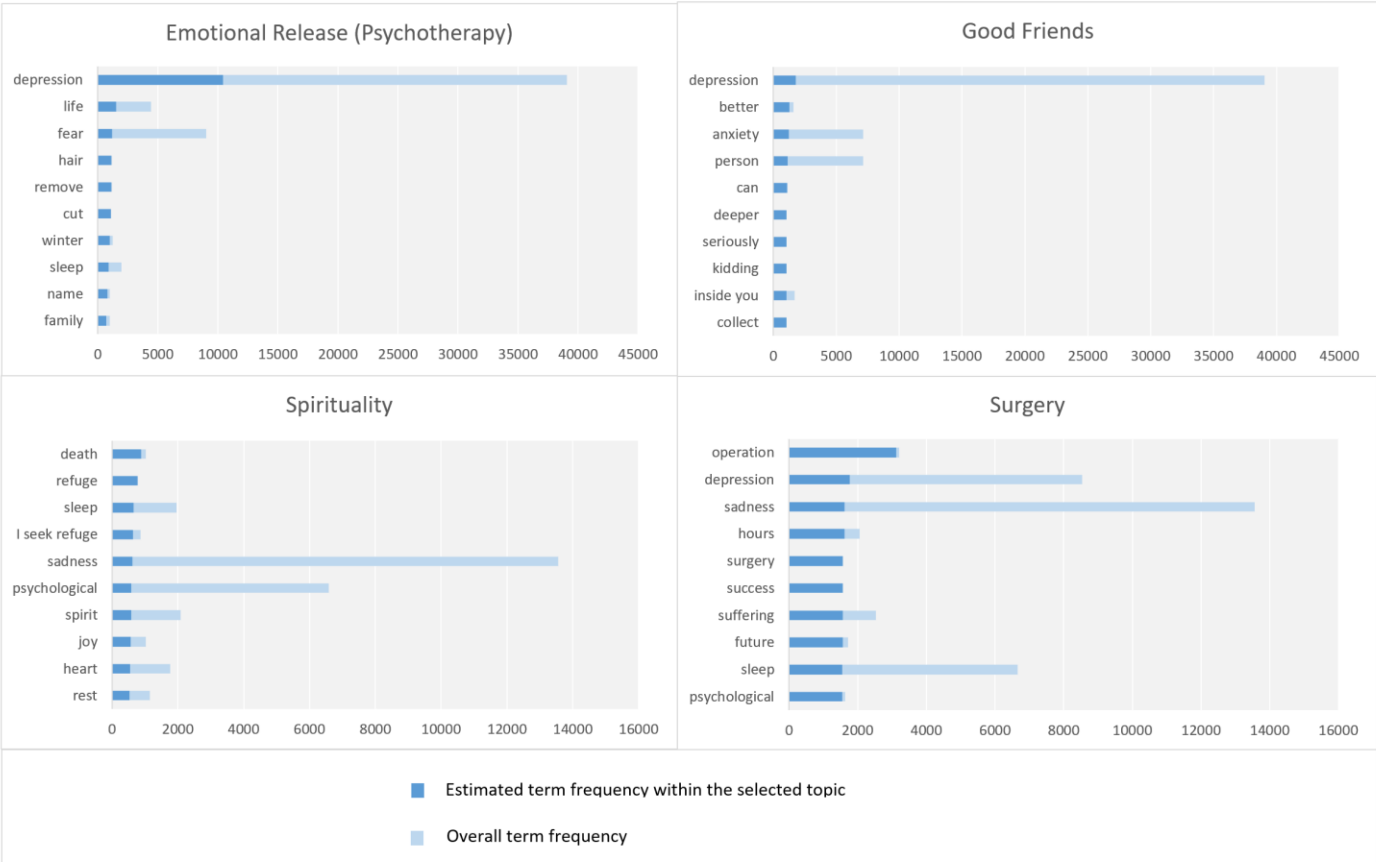

Figure 14. Keyword Frequencies (Macro-Parameter: Treatment Options, Perspective: Causes & Effects); See Figure 21 for keywords in Arabic

5.5.3 Spirituality

This parameter covers spirituality as treatment for psychological illnesses. The parameter contains the following keywords death, refuge, sleep, I seek refuge, sadness, psychological, spirit, joy, heart, rest, life, body, soul, society, anxiety, question, injustice, conditions, blackness, and break. This parameter is similar to a parameter covered in the previous perspective. For further details see Section 4.5.5.

5.5.4 Surgery

This parameter is about surgery as a treatment for psychological diseases. Among the keywords that our model detected are operation, depression, sadness, hours, surgery, success, suffering, future, sleep, psychological, medical, patient, mood, Salman, natural, first, thinking, anxiety, excess, and permanent. Several tweets have talked about the success of a surgical operation to treat a patient suffering from chronic depression.

5.6 Parameter-Drug Associations (Causes & Effects)

Similar to Section 4.7, here we provide the associations between the detected parameters and drugs for the Causes & Effects perspective. These are shown in Table 7 (Column 3) and Figure 15. For example, for the Insomnia parameter, the associated drugs include Cipralex which is an antidepressant. Their association with the Insomnia parameter shows a direct relationship between insomnia and depression in which either one of them can be a trigger for the other [50]. Insomnia, for example, may raise a person's risk of developing depression tenfold compared to people who sleep well at night. On the other hand, depression is linked to sleep problems like getting less beneficial slow wave sleep each night [51]. Moreover, the association between Melatonin and the Insomnia parameter is because people commonly use it for insomnia conditions [52]. Furthermore, we found

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 27 February 2023 doi:10.20944/preprints202301.0415.v2

that some painkillers are associated with the Insomnia parameter such as Panadol. This could be because some people who have some pain or headache and face sleeping difficulties can use painkillers. The procedure to discover the parameter-drug associations was explained in Section 4.7.

Table 7. Parameter-Drug Associations (Perspective: Causes & Effects)

Macro-Parameter	Parameter	Drugs Associated
Diseases & Disorders	Attachment Disorder	No Drugs
	Insomnia	Panadol, Panadol Night, Panadol Extra, Cipralex, Melatonin
	Obsessive Compulsive Disorder (OCD)	Panadol Night
	Post-Surgery Depression	No Drugs
	Chronic Physiological Diseases	Fluoxetine, Sertraline, Citalopram, Lyrica, Melatonin
Individual Factors	Fear	No Drugs
	Sadness	No Drugs
	Loneliness	Cipralex
	Lacking Passion	No Drugs
		No Drugs
	Suppressing Emotions	Wellbutrin, Letrozole, Cabergoline, Imipramine
	Negative Emotions	Panadol
	Devil (Negative Thoughts)	No Drugs
	Lacking Inner Peace	Ashwagandha, Fluoxetine, Sertaline, Venlafaxine
Social & Economic Factors	Study	Clonazepam, Lorazepam, Diazepam, Prozac, Cipralex, Bupropion, Wellbutrin, Ashwagandha
	Work	Seroxat, Melatonin, Panadol Night, Panadol
	Lifestyles	No Drugs
	High Cost of Healthcare	No Drugs
	Seasonal Depression	Panadol, Panadol Night, Melatonin
Treatment Options	Emotional Release (Psychotherapy)	Cipralex, Remeron, Panadol Night, Panadol
	Good Friends	Duspatalin, Panadol Night
	Spirituality	No Drugs
	Surgery	No Drugs

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 27 February 2023 doi:10.20944/preprints202301.0415.v2

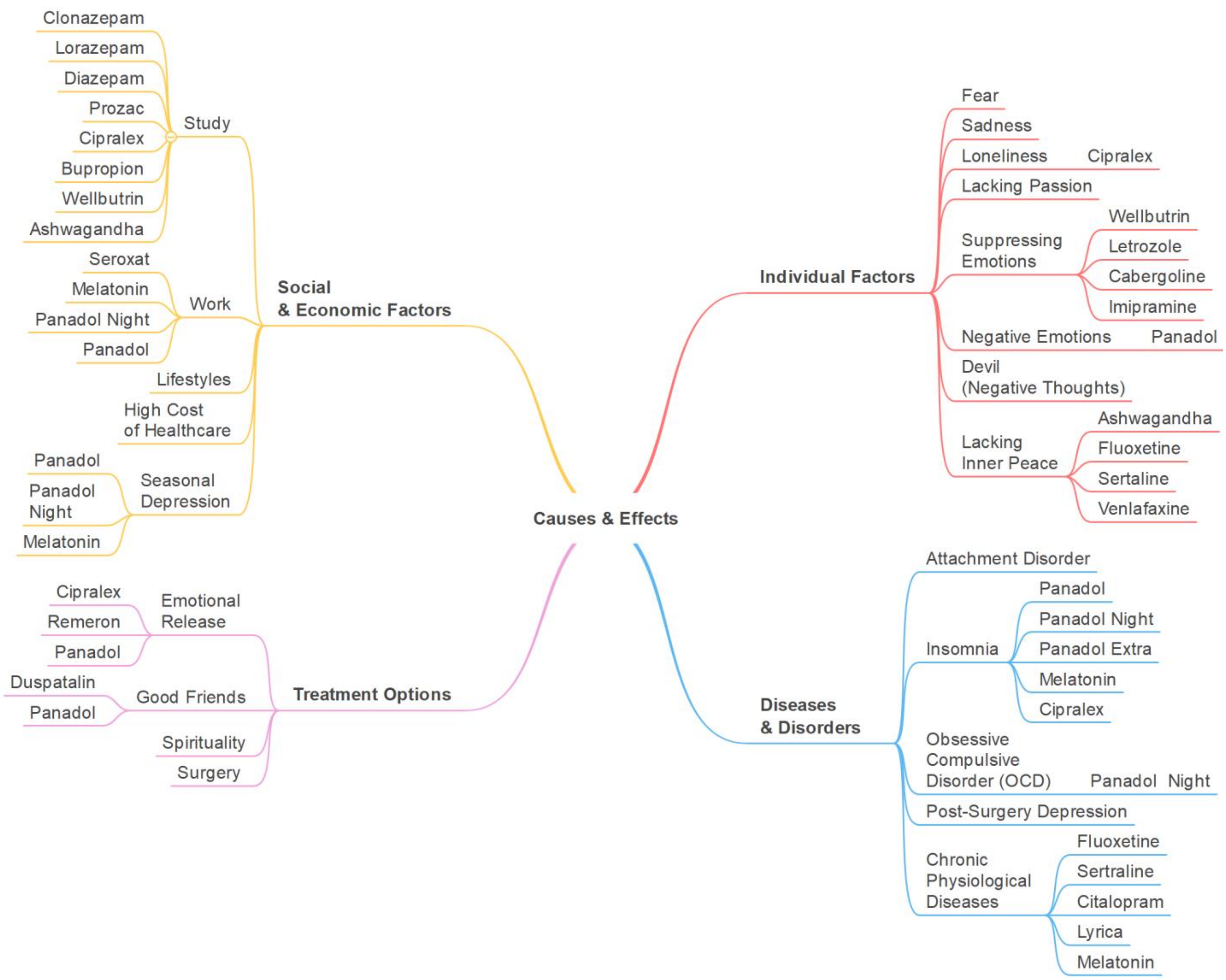

Figure 15. Parameter-Drug Associations Maps (Perspective: Causes & Effects)

6. Parameter Discovery for Psychological Heath (Drug Abuse)

In this section, we discuss the parameters discovered for the Drug Abuse perspective. An overview of parameters and macro-parameters is provided in Section 6.1. The parameters are explained in Section 6.2. In Section 6.3, the associations between the detected parameters and drugs are provided.

6.1 Overview and Taxonomy

In this section, we discuss Drug Abuse perspective. We employed a list of keywords to build a subset of the dataset and identify the parameters for the Drug Abuse perspective (See Table 8). The list includes Arabic and some English keywords because some tweets have English terminology like drug names. The dataset that we got after filtering data contains 2,701 tweets.

Table 8. Keywords Used to Discover Parameters (Perspective: Drug Abuse)

Keywords Used to Discover Parameters for Drug Abuse Perspective
إساءة إستعمال، مزاج، الكيف، نشوة، بدون وصفة، حبة، حبه، حبوب، زايدة، زائدة
abuse, mood, mood, trance, without a recipe, pill, pill, pills, extra, extra

 doi:10.20944/preprints202301.0415.v2

The Latent Dirichlet Allocation (LDA) modelling algorithm detected 30 clusters for Drug Abuse perspective. We excluded twenty clusters from the results as they were irrelevant to the focus of this perspective. We merged similar clusters, also known as parameters. Based on the domain knowledge and some quantitative approaches, the parameters were categorized into five macro-parameters. The methodology and process for discovering and grouping macro-parameters was discussed in Section 3. Table 9 is similar to Table 3, 6 in Section 4.1 and section 5.1, respectively.

Table 9. Macro-Parameters and Parameters (Perspective: Drug Abuse)

Parameter	ID	(%)	Keywords
Bipolar Disorder	1	16.1	كابه، مزاج، حزن، شخص، غريب، لدرجه، لحظه، بحاله، كلمه، ادخل، منطقيه، عشوائيه، وتحولني، وموجات، بطاق، احتاج، دموعي، اللحظات، الاطمئنان، تفهم gloom, mood, sadness, person, strange, degree, moment, condition, word, enter, logical, random, transform, waves, endurance, need, tears, moments, reassurance, understanding
University Exams	2	13.9	ومره، اكتئاب، حاله، طبب، حبوب، عمل، حاولت، للاسف، مساعده، السلام، عبال، انتحر، السجن، اجبب، ورحمه، قص، تعبت، وعندي، صعبه، تراني once, depression, condition, fine, pills, work, tried, unfortunately, help, peace, family, suicide, prison, answer, mercy, cut, tired, have, difficult, see
Death of Loved Ones	6	4.4	حبوب، الاكتئاب، الامر، شعور، فتره، للاكتئاب، بالحياه، افضل، اهم، الدواء، وحتى، وفاه، عاشه، فقدت، للنوم، واذهب، رغبتي، مقاومته، خاركي، مخده pills, depression, matter, feeling, period, depression, life, better, more important, medicine, even, death, lived, lost, sleep, go, desire, resistance, Kharkhi, pillow
Addiction	7 8 24	3.6 3.6 1.5	نشوه، الشخص، شخص، العالم، سعاده، الحقيقه، اهم، المخدرات، الذات، بعيده، وواقعي، بالواقع، اقرب، وضعفه، وثيق، الصحه، معرفه، النرجسي، اتصال، بنقاط trance, the person, person, world, happiness, truth, most important, drugs (illegal drugs), self, far, realistic, fact, closer, weakness, close, health, knowledge, narcissist, connection, dots
Suicide	19 25 28	1.7 1.5 1.3	الاكتئاب، حبوب، النفسيه، الانسان، الامراض، احس، النفسي، الناس، حبه، مزاج، كثير، المرض، اكتئاب، تسبب، مرض، المخ، زائده، ادمان، نفسي، قلق depression, pills, psychological, human, diseases, feel, psychological, people, love, mood, a lot, disease, depression, cause, illness, brain, excess, addiction, psychological, anxiety
Flakka Drug	26	1.5	اكتئاب، خوف، حبه، جرعه، شديد، جديده، تناول، الشعور، المشكله، الرغبه، وحده، وبالتالي، الانسحاب، المخدر، بالخمول، للمخدر، للانسحاب، محاولتك، اعراض، الاكتئاب depression, fear, love, potion, intense, new, take, feeling, problem, desire, alone, therefore, withdrawal, dope, lethargy, drug, to withdraw, attempt, symptoms, depression

Using the discovered parameters for Drug Abuse perspective, a taxonomy was created (see Figure 16).

Figure 16. Taxonomy (Perspective: Drug Abuse)

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 27 February 2023 doi:10.20944/preprints202301.0415.v2

6.2 Drug Abuse

In this section, we discuss the parameters related to the macro-parameter Drug Abuse. Figure 17 shows the top ten key terms, in each parameter in Drug Abuse perspective, according to term frequency (for further details see Section 3.6)

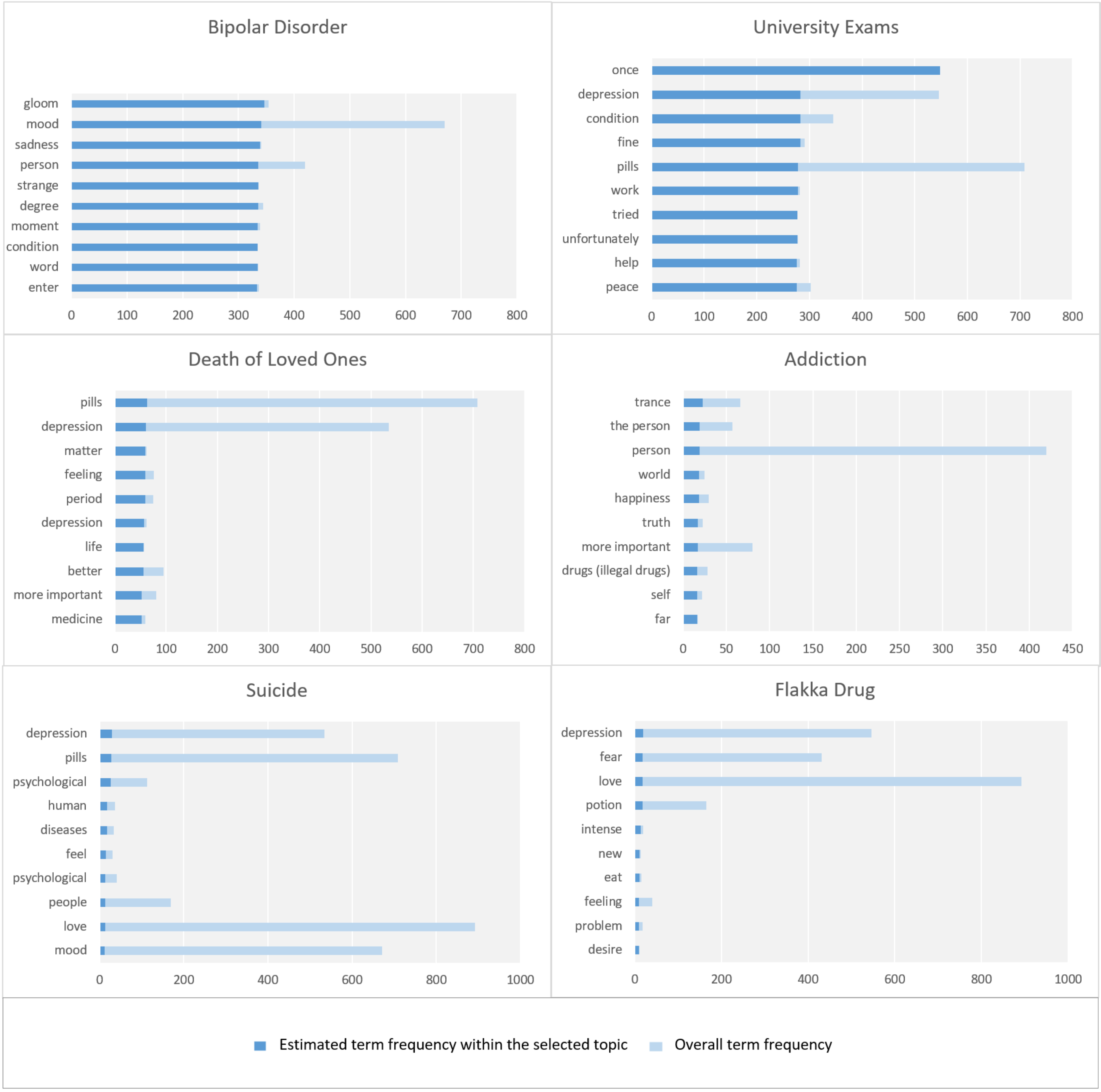

Figure 17. Keyword Frequencies (Macro-Parameter: Drug Abuse, Perspective: Drug Abuse); See Figure 22 for keywords in Arabic

6.2.1 Bipolar Disorder

The parameter relates to bipolar disorder, and it contains the following keywords depression, mood, sadness, person, strange, degree, moment, condition, word, enter,

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 27 February 2023 doi:10.20944/preprints202301.0415.v2

logical, random, transform, waves, endurance, need, tears, moments, reassurance, and understanding.

6.2.2 University Exams

The parameter is regarding university exams, and it is described by the following keywords depression, condition, fine, pills, work, tried, unfortunately, help, peace, family, suicide, prison, answer, mercy, cut, tired, have, difficult, and see.

6.2.3 Death of Loved Ones

The parameter relates to death of loved ones as cause of drug abuse. The following keywords were detected by our model: pills, depression, matter, feeling, period, depression, life, better, more important, medicine, even, death, lived, lost, sleep, go, desire, resistance, Kharkhi, etc. Some tweets relate to depression of football player Inista and the death of his close friend which caused him depression.

6.2.4 Addiction

The parameter discusses addiction, and it is characterized by keywords such as ecstasy, person, person, world, happiness, truth, most important, drug, self, far, realistic, fact, closer, weakness, close, health, knowledge, narcissist, and connection.

6.2.5 Suicide

The parameter is about abusing drugs and committing suicide as an effect of psychological issues. The following keywords were detected by our model: psychological, potion, treatment, heart, one, long, love, doctor, take, pass, fear, depression, bad, etc. Some people mentioned that they have tried to commit suicide by using overdose of medicine.

6.2.6 Flakka Drug

This parameter is about Flakka drug. The following keywords were detected by our model: depression, fear, love, potion, intensity, newness, intake, feeling, problem, desire, alone, therefore, withdrawal, dope, lethargy, drug, to withdraw, attempt, symptoms, depression. Many tweets mentioned that this drug is spread among young people and the reason for its spread is that it is cheap. People have also discussed the effects of using Flakka drug such as hallucinations, madness, strange behavior, loss of control over mental abilities, and a mad start to a dark path. Many tweets have also mentioned the withdrawal symptoms of the drug such as feeling lethargy and suffering severe depression.

6.3 Parameter-Drug Associations (Drug Abuse)

This section highlights the associations between the detected parameters and drugs for the Drug Abuse perspective. Figure 18 shows a taxonomy of associations between detected parameters and the drugs detected automatically by our tool. For example, in the figure, the Flakka drug is associated with the Flakka Drug parameter, which is a dangerous synthetic cathinone [53]. Also, the Melatonin drug is associated with the Addiction parameter. This could be because Melatonin can be used in addiction management [54]. Escitalopram is also associated with the Addiction parameter which is an antidepressant and it can be used in the recovery stage from addiction [55].

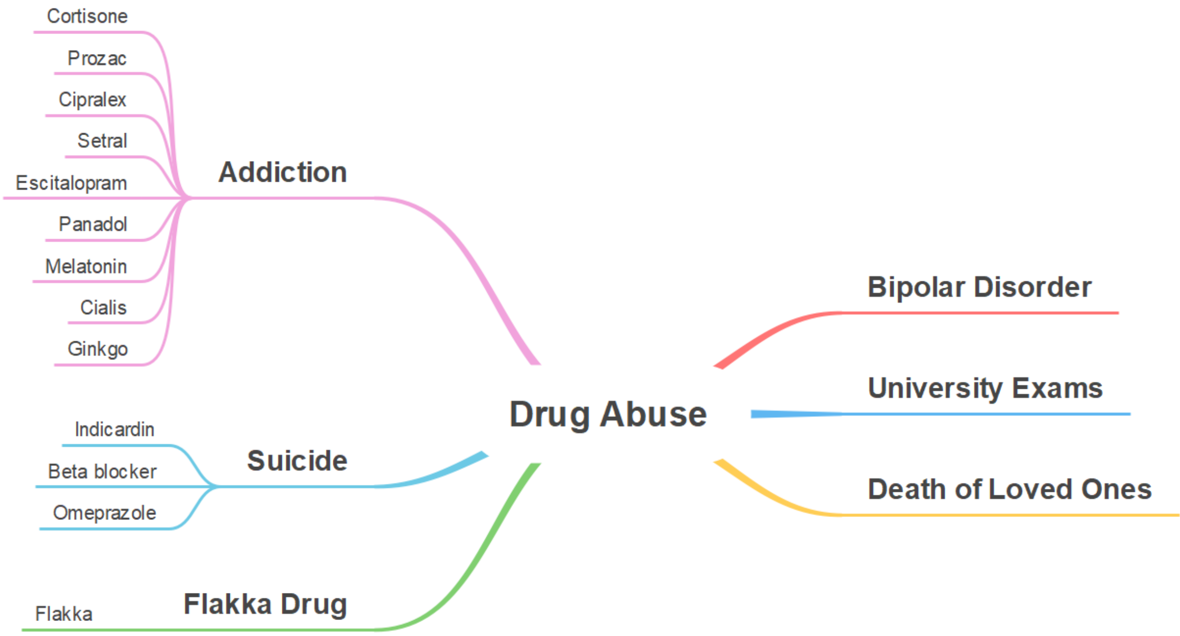

Figure 18. Parameter-Drug Associations Maps (Perspective: Drug Abuse)

7. Discussion

In this research, we proposed a big data and machine learning-based approach for the automatic discovery of parameters related to psychological health from Twitter data. The parameters are discovered from three different perspectives Drugs & Treatments, Causes & Effects, and Drug Abuse. Moreover, we automatically discovered associations between the parameters and drugs. The parameters were discussed in detail in Sections 4-6, respectively. We discussed the use of Twitter to automatically discover what drugs are used for psychological health, what are causes and effects of psychological issues, what are the side effects of drugs, and how drugs are abused.

We discovered twenty-four parameters from the Drugs & Treatments perspective and grouped them into five macro-parameters: Diseases & Disorders, Individual Factors, Social & Economic Factors, Treatment Options, and Treatment Limitations. A total of twenty-two parameters were detected from the Causes & Effects perspective and we grouped them into four macro-parameters. These are Diseases & Disorders, Individual Factors, Social and Economic Factors, and Treatment Options. We detected six parameters from Drug Abuse perspective, namely, Bipolar Disorder, University Exams, Death of Loved Ones, Addiction, Suicide, and Flakka Drug.

A multi-perspective view of psychological health data is depicted in Figure 19. It is a combination of all three perspectives: Drugs & Treatments, Causes & Effects, and Drug Abuse. It includes six macro-parameters: Diseases & Disorders, Individual Factors, Social and Economic Factors, Treatment Options, Treatment Limitations, and Drug Abuse. We merged similar macro-parameters together. For example, we have two Diseases & Disorders macro-parameters, one from Drugs & Treatments perspective with one parameter (Postpartum Depression), and another one from Causes & Effects perspective with five parameters (Attachment Disorder, Insomnia, Obsessive Compulsive Disorder (OCD), Post-Surgery Depression, and Chronic physiological Diseases). We merged all these parameters in one Diseases & Disorders macro-parameter as shown in Figure 19.

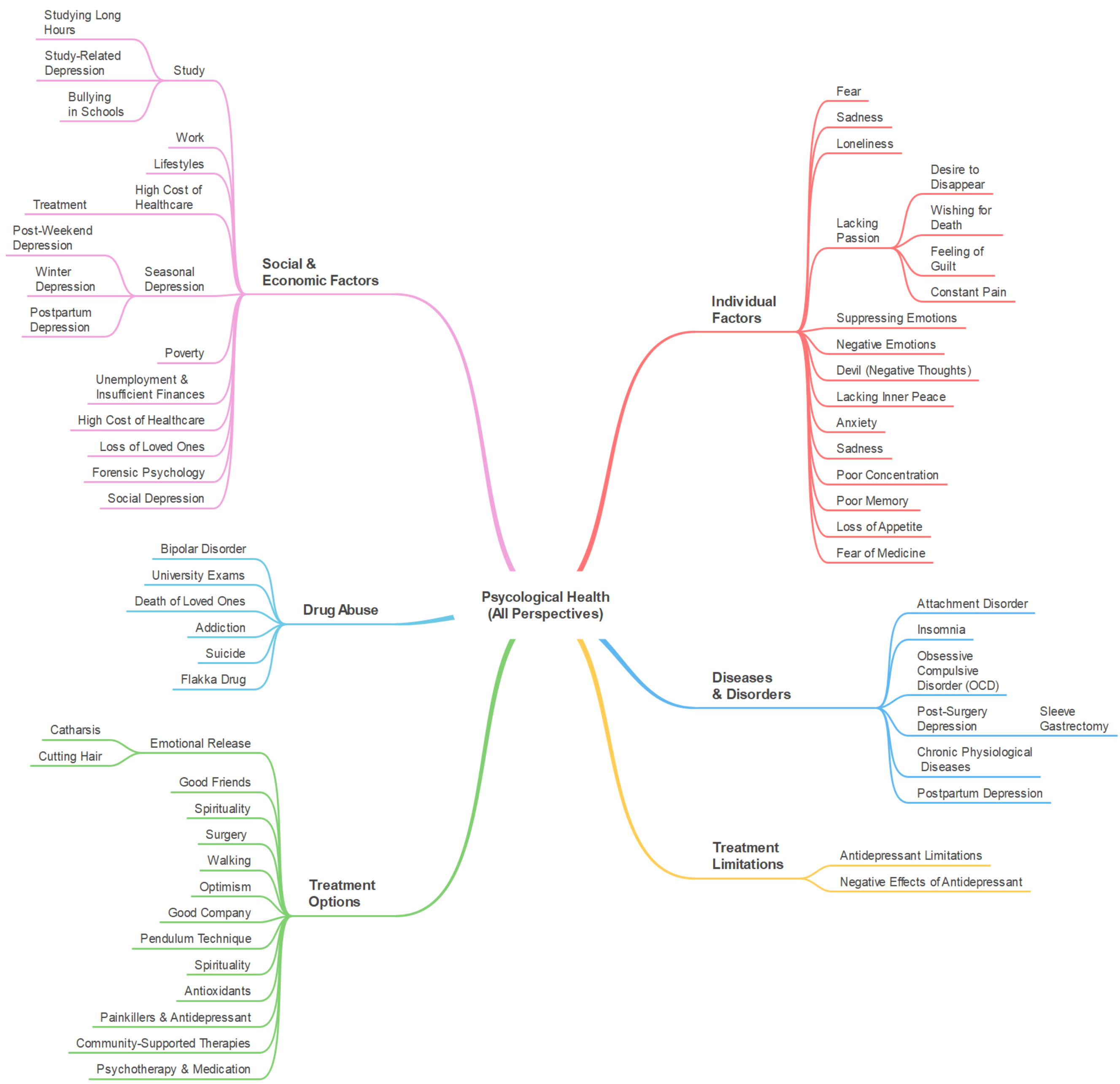

Figure 19. Taxonomy (Perspectives: Drugs & Treatments, Causes & Effects, and Drug Abuse)

This work makes important theoretical and practical contributions to the area. The earlier research (see Section 2) has looked into the relation between physical illnesses and mental health, specific mental health disorders and factors, effects of education on mental health, CVOID-19 and mental health, machine learning in mental health, and the use of Twitter data in mental health. This study offers a comprehensive examination of mental health, including causes, treatments, and the impact of drug use and abuse, as seen on Twitter and discussed by both the public and health professionals. Additionally, the study identified associations between various drugs and mental health. This is the first study to take such a holistic approach to understanding mental health. The findings have the potential to open new avenues for identifying drug use and abuse for mental health, as well as other micro and macro factors related to mental health through social media. The methodology can also be applied to other diseases and may have potential for forensic toxicology research. However, more research is needed to fully explore the potential of social media for forensic purposes. The work presented in this paper is the beginning, many more works are needed to investigate the potential of social media for forensic purposes. It is part of our broader work on data-driven parameter discovery from Twitter and other data sources applied previously to different research areas including the education sector in KSA during COVID-19 [33], the discovery of cancer-related healthcare services [56], families and smart homes [57], transportation [58], and COVID-19 governance measures [59].

8. Conclusion

Mental health issues can have significant impacts on individuals and communities and addressing root causes can help prevent mental health problems. The big data and machine learning approach proposed in this paper can be used to automatically discover parameters related to mental health from Twitter data, including information on drugs and treatments, causes and effects, and drug abuse. This can provide a comprehensive understanding of mental health as seen on social media, discussed by the public and health professionals, and can also identify associations with different drugs. The methodology can be extended to other diseases and has the potential for discovering evidence for forensic toxicology from social and digital media. Additional research is necessary to fully explore the potential of social media for forensic purposes, as this paper is just the beginning, and this will form our future work.

Author Contributions: "Conceptualization, S.A., and R.M.; methodology, S.A., and R.M.; software, S.A.; validation, S.A., and R.M.; formal analysis, S.A., R.M., I.K, and S.M.A; investigation, S.A., R.M., I.K., and S.M.A; resources, R.M., and I.K.; data curation, S.A.; writing—original draft preparation, S.A., and R.M.; writing—review and editing, R.M., I.K, and S.M.A; visualization, S.A.; supervision, R.M. and I.K.; project administration, R.M. and I.K.; funding acquisition, R.M. and I.K. All authors have read and agreed to the published version of the manuscript.".

Funding: The authors acknowledge with thanks the technical and financial support from the Deanship of Scientific Research (DSR) at the King Abdulaziz University (KAU), Jeddah, Saudi Arabia, under Grant No. RG-6-611-40.

Acknowledgments: The work carried out in this paper is supported by the HPC Center at the King Abdulaziz University. The training and software development work reported in this paper was carried out on the Aziz supercomputer.

Conflicts of Interest: The authors declare no conflict of interest.

References

[1] A. A. Alaql, F. AlQurashi, and R. Mehmood, "Data-Driven Deep Journalism to Discover Age Dynamics in Multi-Generational Labour Markets from LinkedIn Media," Oct. 2022, doi: 10.20944/PREPRINTS202210.0472.V1.

[2] R. Dybdahl and L. Lien, "Mental health is an integral part of the sustainable development goals." 2017.

[3] X. Xu, S. S. Shrestha, K. F. Trivers, L. Neff, B. S. Armour, and B. A. King, "U.S. healthcare spending attributable to cigarette smoking in 2014," *Preventive Medicine*, vol. 150. Academic Press Inc., 2021. doi: 10.1016/J.YPMED.2021.106529.

[4] "Addiction Statistics | Drug & Substance Abuse Statistics."

[5] H. Schächinger, M. Grob, R. Ritz, and M. Solér, "Mental stress increases right heart afterload in severe pulmonary hypertension," *Clinical Physiology*, vol. 20, no. 6, pp. 483–487, Nov. 2000, doi: 10.1046/J.1365-2281.2000.00287.X.

[6] E. Volpato, S. Toniolo, F. Pagnini, and P. Banfi, "The Relationship Between Anxiety, Depression and Treatment Adherence in Chronic Obstructive Pulmonary Disease: A Systematic Review," *Int J Chron Obstruct Pulmon Dis*, vol. 16, pp. 2001–2021, Jul. 2021, doi: 10.2147/COPD.S313841.

[7] S. Ç. Altuntaś and Ç. Hocaoğlu, "Effects of Chronic Suppression or Oversuppression of Thyroid-Stimulating Hormone on Psychological Symptoms and Sleep Quality in Patients with Differentiated Thyroid Cancer," *Hormone and Metabolic Research*, vol. 53, no. 10, pp. 683–691, Oct. 2021, doi: 10.1055/A-1639-1024/ID/R2021-07-0194-0021.

[8] M. Rodriguez-Ayllon *et al.*, "Physical fitness and psychological health in overweight/obese children: A cross-sectional study from the ActiveBrains project," *J Sci Med Sport*, vol. 21, no. 2, pp. 179–184, Feb. 2018, doi: 10.1016/J.JSAMS.2017.09.019.

[9] A. S. Tubbs, W. Khader, F. Fernandez, and M. A. Grandner, "The common denominators of sleep, obesity, and psychopathology," *Curr Opin Psychol*, vol. 34, pp. 84–88, Aug. 2020, doi: 10.1016/J.COPSYC.2019.11.003.

[10] G. M. J. Taylor and J. L. Treur, "An application of the stress-diathesis model: A review about the association between smoking tobacco, smoking cessation, and mental health," *International Journal of Clinical and Health Psychology*, vol. 23, no. 1, p. 100335, Jan. 2023, doi: 10.1016/J.IJCHP.2022.100335.

[11] X. Jing, L. Lu, and Y. Yao, "Personality modifies the effect of post-traumatic stress disorder (PTSD) and society support on depression-anxiety-stress in the residents undergone catastrophic flooding in Henan, China," *Med Pr*, vol. 73, no. 4, pp. 305–314, Sep. 2022, doi: 10.13075/MP.5893.01254.

[12] G. Ramirez, S. Y. Hooper, N. B. Kersting, R. Ferguson, and D. Yeager, "Teacher Math Anxiety Relates to Adolescent Students' Math Achievement," *AERA Open*, vol. 4, no. 1, Jan. 2018, doi: 10.1177/2332858418756052/ASSET/IMAGES/LARGE/10.1177_2332858418756052-FIG2.JPEG.

[13] N. Salari *et al.*, "Prevalence of stress, anxiety, depression among the general population during the COVID-19 pandemic: A systematic review and meta-analysis," *Global Health*, vol. 16, no. 1, pp. 1–11, Jul. 2020, doi: 10.1186/S12992-020-00589-W/TABLES/2.

[14] C. Zhang *et al.*, "The Psychological Impact of the COVID-19 Pandemic on Teenagers in China," *Journal of Adolescent Health*, vol. 67, no. 6, pp. 747–755, 2020, doi: 10.1016/j.jadohealth.2020.08.026.

[15] S. Alswedani, R. Mehmood, I. Katib, and S. M. Altowaijri, "Psychological Health and Drugs: Data-Driven Discovery of Causes, Treatments, Effects, and Abuses," *Preprints (Basel)*, Jan. 2023.

[16] V. Hagger *et al.*, "Diabetes MILES Youth-Australia: Methods and sample characteristics of a national survey of the psychological aspects of living with type 1 diabetes in Australian youth and their parents," *BMC Psychol*, vol. 4, no. 1, pp. 1–13, Aug. 2016, doi: 10.1186/S40359-016-0149-9/TABLES/2.

[17] A. M. Schmidt, S. D. Golden, N. C. Gottfredson, S. T. Ennett, A. E. Aiello, and K. M. Ribisl, "Psychological Health and Smoking in Young Adulthood," *https://doi.org/10.1177/2167696819858812*, vol. 9, no. 4, pp. 320–329, Jul. 2019, doi: 10.1177/2167696819858812.

[18] X. Wang, C. Zhang, Y. Ji, L. Sun, L. Wu, and Z. Bao, "A Depression Detection Model Based on Sentiment Analysis in Micro-blog Social Network BT - Trends and Applications in Knowledge Discovery and Data Mining," 2013, pp. 201–213.

[19] J. D. Bremner, "Traumatic stress: effects on the brain," *Dialogues Clin Neurosci*, vol. 8, no. 4, pp. 445–461, 2022, doi: 10.31887/DCNS.2006.8.4/JBREMNER.

[20] S. Kellett, C. Bee, V. Aadahl, E. Headley, and J. Delgadillo, "A pragmatic patient preference trial of cognitive behavioural versus cognitive analytic guided self-help for anxiety disorders," *Behavioural and Cognitive Psychotherapy*, vol. 49, no. 1, pp. 104–111, Jan. 2021, doi: 10.1017/S1352465820000442.

[21] N. Daviu, M. R. Bruchas, B. Moghaddam, C. Sandi, and A. Beyeler, "Neurobiological links between stress and anxiety," *Neurobiol Stress*, vol. 11, p. 100191, Nov. 2019, doi: 10.1016/J.YNSTR.2019.100191.

[22] T. M. Karrer *et al.*, "Brain-based ranking of cognitive domains to predict schizophrenia," *Hum Brain Mapp*, vol. 40, no. 15, pp. 4487–4507, Oct. 2019, doi: 10.1002/HBM.24716.

[23] N. Çelik, B. Ceylan, A. Ünsal, and Ö. Çağan, "Depression in health college students: relationship factors and sleep quality," *https://doi.org/10.1080/13548506.2018.1546881*, vol. 24, no. 5, pp. 625–630, May 2018, doi: 10.1080/13548506.2018.1546881.

[24] A. Kirubasankar, P. Nagarajan, P. Kandasamy, and S. Kattimani, "More students with anxiety disorders in urban schools than in rural schools: A comparative study from Union Territory, India," *Asian J Psychiatr*, vol. 56, p. 102529, Feb. 2021, doi: 10.1016/J.AJP.2020.102529.

[25] Y. Mao, N. Zhang, J. Liu, B. Zhu, R. He, and X. Wang, "A systematic review of depression and anxiety in medical students in China," *BMC Med Educ*, vol. 19, no. 1, pp. 1–13, Sep. 2019, doi: 10.1186/S12909-019-1744-2/FIGURES/3.

[26] T. T. C. Quek *et al.*, "The Global Prevalence of Anxiety Among Medical Students: A Meta-Analysis," *International Journal of Environmental Research and Public Health 2019, Vol. 16, Page 2735*, vol. 16, no. 15, p. 2735, Jul. 2019, doi: 10.3390/IJERPH16152735.

[27] V. Capone, M. Joshanloo, and M. S. A. Park, "Burnout, depression, efficacy beliefs, and work-related variables among school teachers," *Int J Educ Res*, vol. 95, pp. 97–108, Jan. 2019, doi: 10.1016/J.IJER.2019.02.001.

[28] L. Jeon, C. K. Buettner, and A. A. Grant, "Early Childhood Teachers' Psychological Well-Being: Exploring Potential Predictors of Depression, Stress, and Emotional Exhaustion," *Early Educ Dev*, vol. 29, no. 1, pp. 53–69, Jan. 2017, doi: 10.1080/10409289.2017.1341806.

[29] V. Gianfredi, S. Provenzano, and O. E. Santangelo, "What can internet users' behaviours reveal about the mental health impacts of the COVID-19 pandemic? A systematic review," *Public Health*, vol. 198, pp. 44–52, Sep. 2021, doi: 10.1016/J.PUHE.2021.06.024.

[30] Y. Ding and T. Wang, "Mental Health Management of English Teachers in English Teaching Under the COVID-19 Era," *Front Psychol*, vol. 13, p. 2595, Jun. 2022, doi: 10.3389/FPSYG.2022.916886/BIBTEX.

[31] J. F. Huckins *et al.*, "Mental health and behavior of college students during the early phases of the COVID-19 pandemic: Longitudinal smartphone and ecological momentary assessment study," *J Med Internet Res*, vol. 22, no. 6, 2020, doi: 10.2196/20185.

[32] S. J. Zhou *et al.*, "Prevalence and socio-demographic correlates of psychological health problems in Chinese adolescents during the outbreak of COVID-19," *Eur Child Adolesc Psychiatry*, vol. 29, no. 6, pp. 749–758, 2020, doi: 10.1007/s00787-020-01541-4.

[33] S. Alswedani, R. Mehmood, and I. Katib, "Sustainable Participatory Governance: Data-Driven Discovery of Parameters for Planning Online and In-Class Education in Saudi Arabia During COVID-19," *Frontiers in Sustainable Cities*, vol. 4, p. 97, Jul. 2022, doi: 10.3389/FRSC.2022.871171/BIBTEX.

[34] S. Alswedani, I. Katib, E. Abozinadah, and R. Mehmood, "Discovering Urban Governance Parameters for Online Learning in Saudi Arabia During COVID-19 Using Topic Modeling of Twitter Data," *Frontiers in Sustainable Cities*, vol. 4, p. 66, Jun. 2022, doi: 10.3389/FRSC.2022.751681/BIBTEX.

[35] M. H. E. M. Browning *et al.*, "Psychological impacts from COVID-19 among university students: Risk factors across seven states in the United States," *PLoS One*, vol. 16, no. 1, p. e0245327, 2021, doi: 10.1371/JOURNAL.PONE.0245327.

[36] Y. Zhang, H. Lyu, Y. Liu, X. Zhang, Y. Wang, and J. Luo, "Monitoring Depression Trends on Twitter During the COVID-19 Pandemic: Observational Study," *JMIR Infodemiology* , vol. 1, no. 1, Jul. 2021, doi: 10.2196/26769.

[37] I. Fatima, H. Mukhtar, H. F. Ahmad, and K. Rajpoot, "Analysis of user-generated content from online social communities to characterise and predict depression degree," *https://doi.org/10.1177/0165551517740835*, vol. 44, no. 5, pp. 683–695, Nov. 2017, doi: 10.1177/0165551517740835.

[38] M. R. Islam, M. A. Kabir, A. Ahmed, A. R. M. Kamal, H. Wang, and A. Ulhaq, "Depression detection from social network data using machine learning techniques," *Health Inf Sci Syst*, vol. 6, no. 1, pp. 1–12, Dec. 2018, doi: 10.1007/S13755-018-0046-0/METRICS.

[39] X. Wang, C. Zhang, Y. Ji, L. Sun, L. Wu, and Z. Bao, "A depression detection model based on sentiment analysis in micro-blog social network," *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, vol. 7867 LNAI, pp. 201–213, 2013, doi: 10.1007/978-3-642-40319-4_18/COVER.

[40] N. Fatimah, I. Budi, A. B. Santoso, and P. K. Putra, "Analysis of Mental Health During the Covid-19 Pandemic in Indonesia using Twitter Data," *Proceedings - 2021 8th International Conference on Advanced Informatics: Concepts, Theory, and Application, ICAICTA 2021*, 2021, doi: 10.1109/ICAICTA53211.2021.9640265.

[41] L. Tong *et al.*, "Cost-sensitive Boosting Pruning Trees for depression detection on Twitter," *IEEE Trans Affect Comput*, pp. 1–1, Jan. 2022, doi: 10.1109/TAFFC.2022.3145634.

[42] X. Chen, M. D. Sykora, T. W. Jackson, and S. Elayan, "What about Mood Swings: Identifying Depression on Twitter with Temporal Measures of Emotions," *The Web Conference 2018 - Companion of the World Wide Web Conference, WWW 2018*, pp. 1653–1660, Apr. 2018, doi: 10.1145/3184558.3191624.

[43] N. H. Ismail, N. Liu, M. Du, Z. He, and X. Hu, "A deep learning approach for identifying cancer survivors living with post-traumatic stress disorder on Twitter," *BMC Med Inform Decis Mak*, vol. 20, no. 4, pp. 1–11, Dec. 2020, doi: 10.1186/S12911-020-01272-1/TABLES/5.

[44] K. Roy, U. Lokala, V. Khandelwal, and A. Sheth, "'Is depression related to cannabis?': A knowledge-infused model for Entity and Relation Extraction with Limited Supervision," *CEUR Workshop Proc*, vol. 2846, Feb. 2021, doi: 10.48550/arxiv.2102.01222.

[45] E. Alabdulkreem, "Prediction of depressed Arab women using their tweets," *https://doi.org/10.1080/12460125.2020.1859745*, vol. 30, no. 2–3, pp. 102–117, 2020, doi: 10.1080/12460125.2020.1859745.

[46] S. Almouzini, M. Khemakhem, and A. Alageel, "Detecting Arabic Depressed Users from Twitter Data," *Procedia Comput Sci*, vol. 163, pp. 257–265, Jan. 2019, doi: 10.1016/J.PROCS.2019.12.107.

[47] C. Sievert and K. E. Shirley, "LDAvis: A method for visualizing and interpreting topics," pp. 63–70, 2014.

[48] C. Sievert and K. E. Shirley, "LDAvis: A method for visualizing and interpreting topics," pp. 63–70, 2014.

[49] "pyLDAvis — pyLDAvis 2.1.2 documentation." https://pyldavis.readthedocs.io/en/latest/readme.html (accessed Mar. 16, 2022).

[50] R. M. Benca and M. J. Peterson, "Insomnia and depression," *Sleep Med*, vol. 9, no. SUPPL. 1, pp. S3–S9, Sep. 2008, doi: 10.1016/S1389-9457(08)70010-8.

[51] Johns Hopkins Medicine, "Depression and Sleep: Understanding the Connection ." https://www.hopkinsmedicine.org/health/wellness-and-prevention/depression-and-sleep-understanding-the-connection (accessed Dec. 25, 2022).

[52] Mayo Clinic, "Melatonin ." https://www.mayoclinic.org/drugs-supplements-melatonin/art-20363071 (accessed Dec. 25, 2022).

[53] J. Patocka *et al.*, "Flakka: New Dangerous Synthetic Cathinone on the Drug Scene," *International Journal of Molecular Sciences 2020, Vol. 21, Page 8185*, vol. 21, no. 21, p. 8185, Oct. 2020, doi: 10.3390/IJMS21218185.

[54] O. J. Onaolapo and A. Y. Onaolapo, "Melatonin in drug addiction and addiction management: Exploring an evolving multidimensional relationship," *World J Psychiatry*, vol. 8, no. 2, p. 64, Jun. 2018, doi: 10.5498/WJP.V8.I2.64.

[55] J. Song *et al.*, "Comparative study of the effects of bupropion and escitalopram on Internet gaming disorder," *Psychiatry Clin Neurosci*, vol. 70, no. 11, pp. 527–535, Nov. 2016, doi: 10.1111/PCN.12429.

[56] N. Alahmari, S. Alswedani, A. Alzahrani, I. Katib, A. Albeshri, and R. Mehmood, "Musawah: A Data-Driven AI Approach and Tool to Co-Create Healthcare Services with a Case Study on Cancer Disease in Saudi Arabia," *Sustainability 2022, Vol. 14, Page 3313*, vol. 14, no. 6, p. 3313, Mar. 2022, doi: 10.3390/SU14063313.

[57] G. E. Veselov *et al.*, "Smart Homes and Families to Enable Sustainable Societies: A Data-Driven Approach for Multi-Perspective Parameter Discovery Using BERT Modelling," *Sustainability 2022, Vol. 14, Page 13534*, vol. 14, no. 20, p. 13534, Oct. 2022, doi: 10.3390/SU142013534.

[58] T. Yigitcanlar, M. Wilson, I. Ahmad, F. Alqurashi, E. Abozinadah, and R. Mehmood, "Deep Journalism and DeepJournal V1.0: A Data-Driven Deep Learning Approach to Discover Parameters for Transportation," *Sustainability 2022, Vol. 14, Page 5711*, vol. 14, no. 9, p. 5711, May 2022, doi: 10.3390/SU14095711.

[59] E. Alomari, I. Katib, A. Albeshri, and R. Mehmood, "COVID-19: Detecting Government Pandemic Measures and Public Concerns from Twitter Arabic Data Using Distributed Machine Learning," *International Journal of Environmental Research and Public Health 2021, Vol. 18, Page 282*, vol. 18, no. 1, p. 282, Jan. 2021, doi: 10.3390/IJERPH18010282.

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 27 February 2023 doi:10.20944/preprints202301.0415.v2

Appendix: Figures with Arabic Keywords

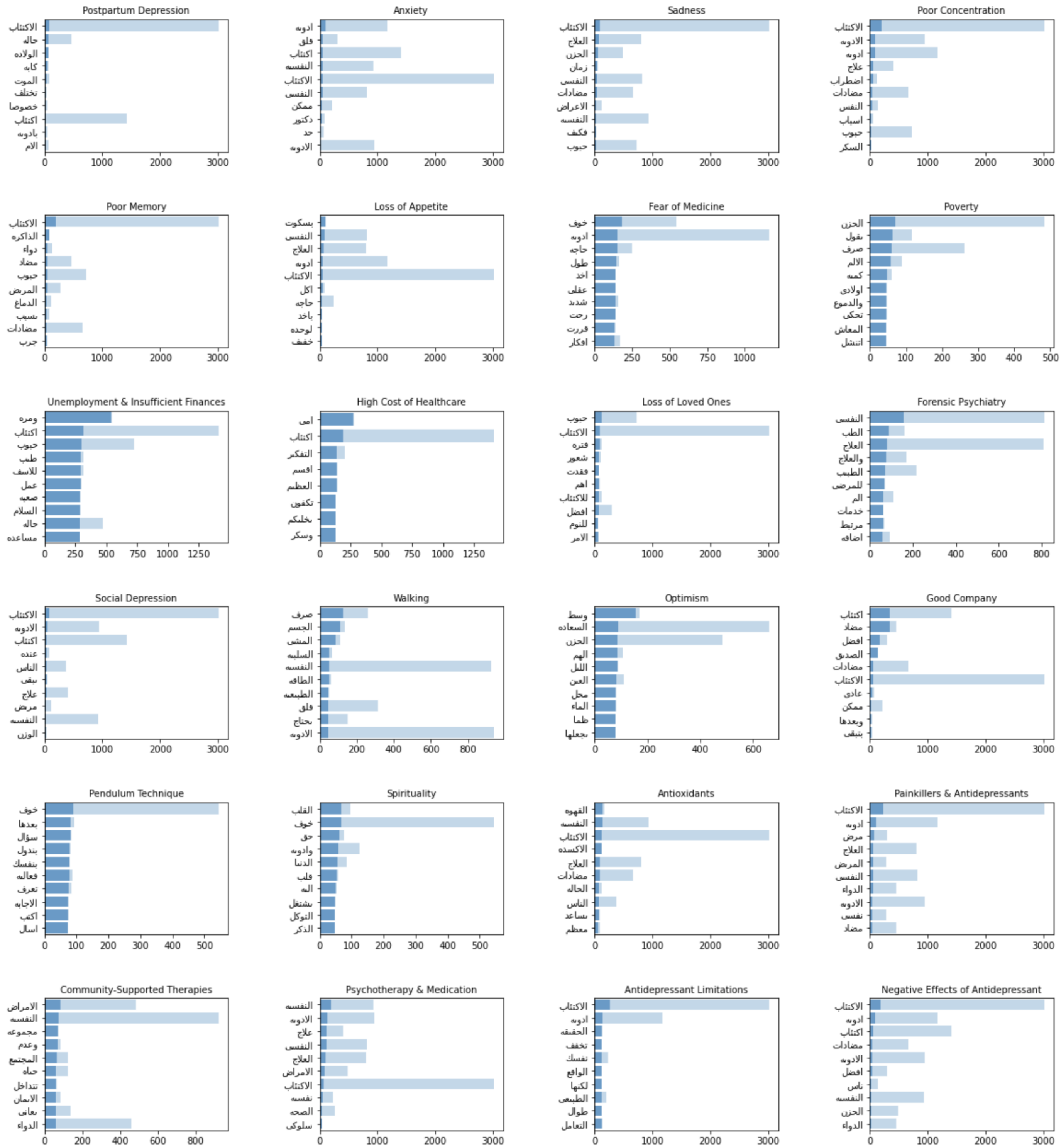

Figure 20. Keyword Frequencies (Perspective: Drugs & Treatments) (x-axis: Frequency, y-axis: Keywords)

 doi:10.20944/preprints202301.0415.v2

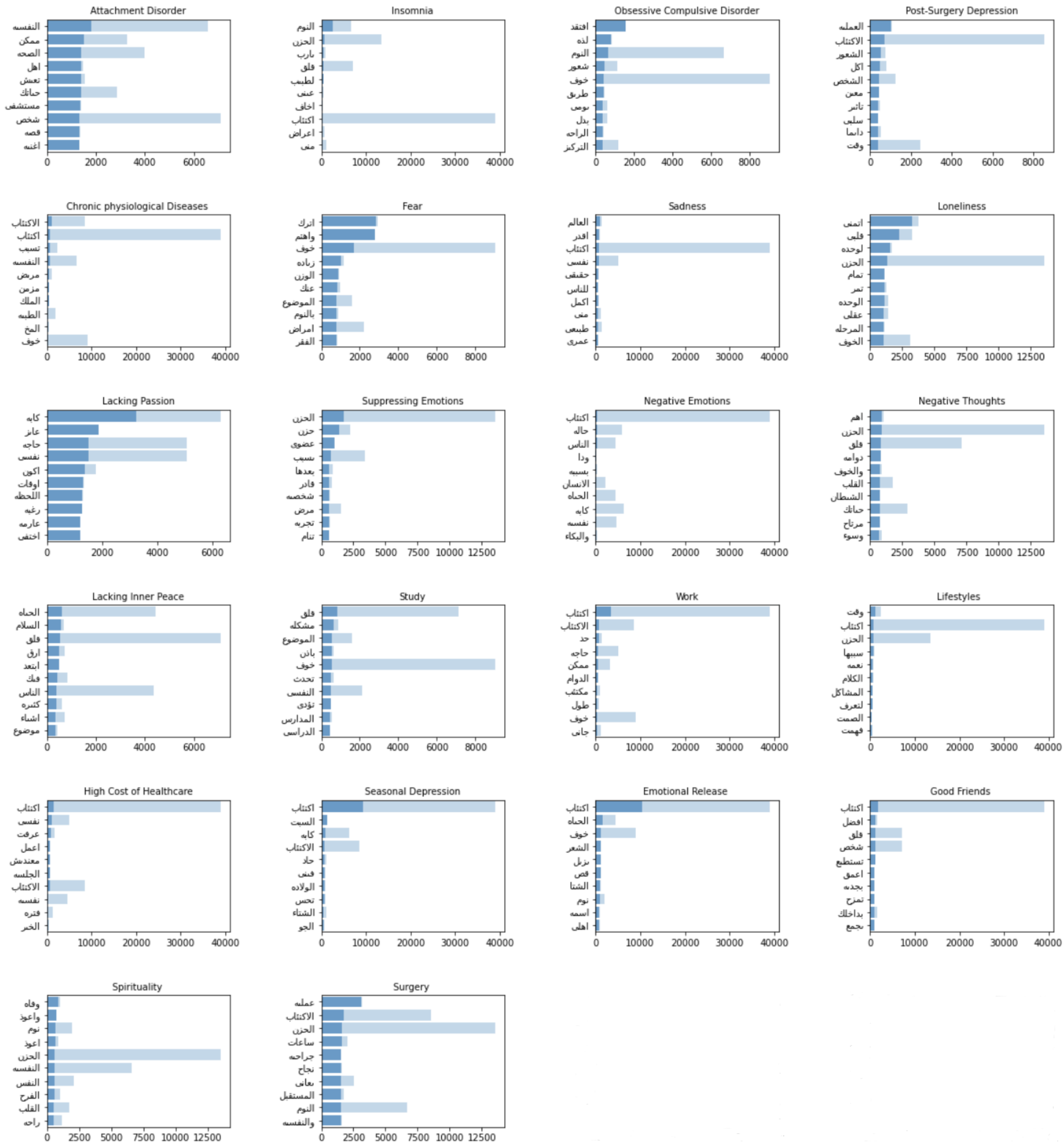

Figure 21. Keyword Frequencies (Perspective: Causes & Effects) (x-axis: Frequency, y-axis: Keywords)

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 27 February 2023 doi:10.20944/preprints202301.0415.v2

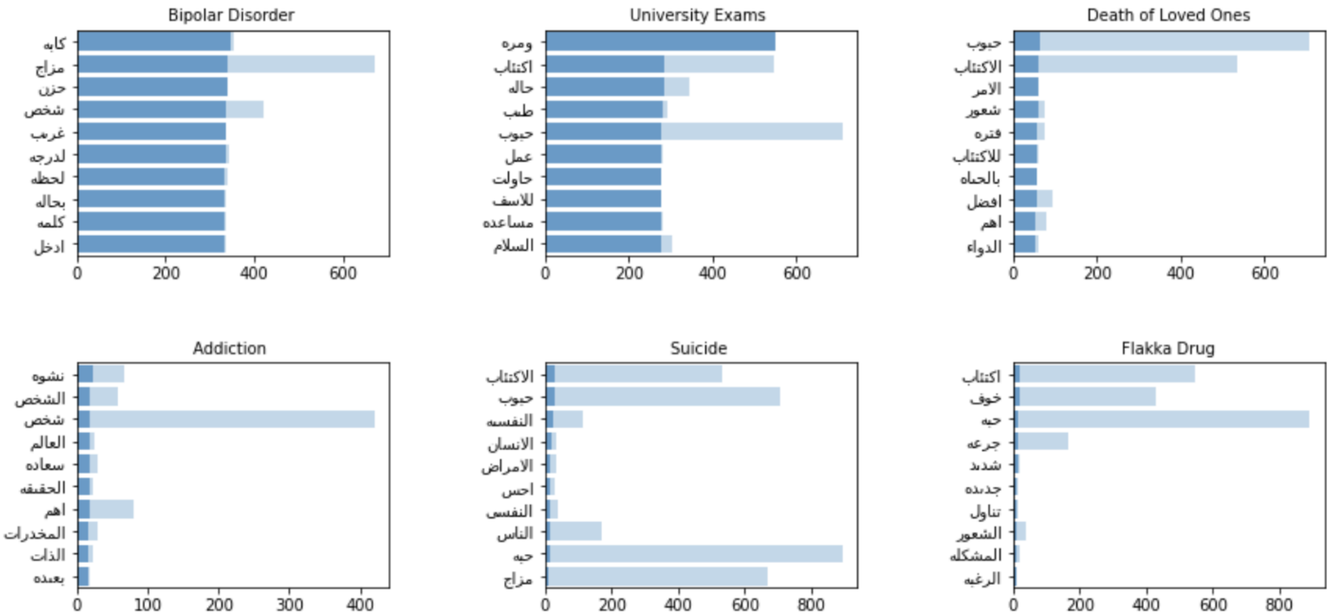

Figure 22. Keyword Frequencies (Perspective: Drug Abuse) (x-axis: Frequency, y-axis: Keywords)

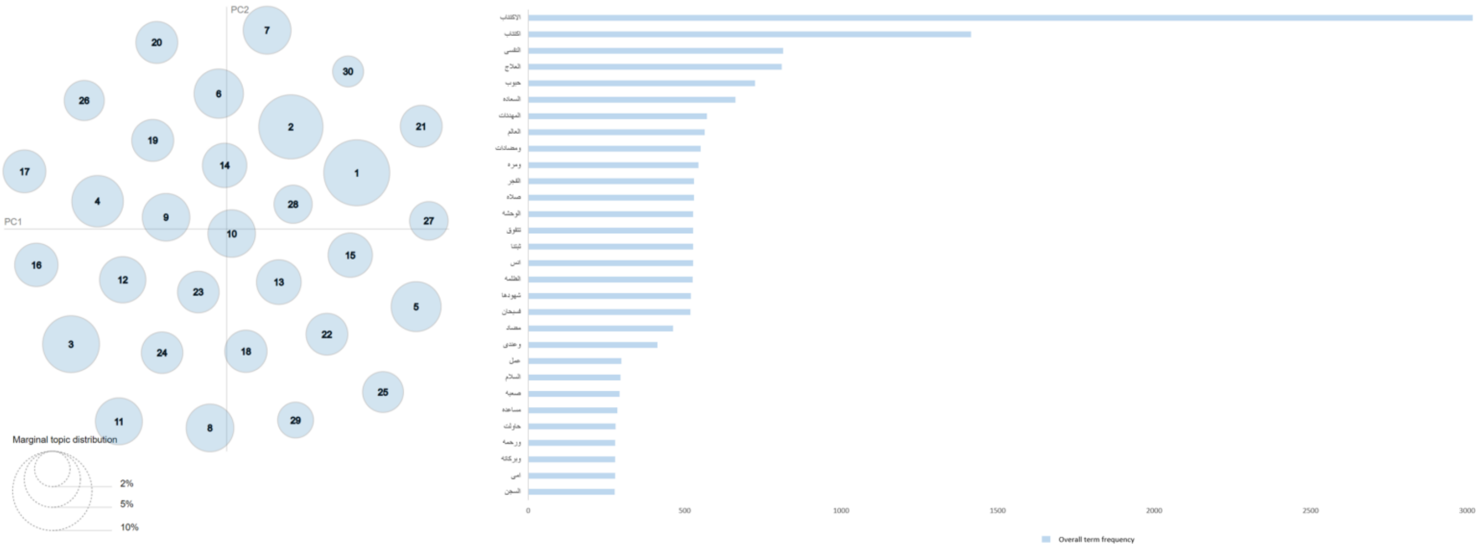

Figure 23. The Intertopic Distance Map of the parameters (Perspective: Drugs & Treatments)

 doi:10.20944/preprints202301.0415.v2

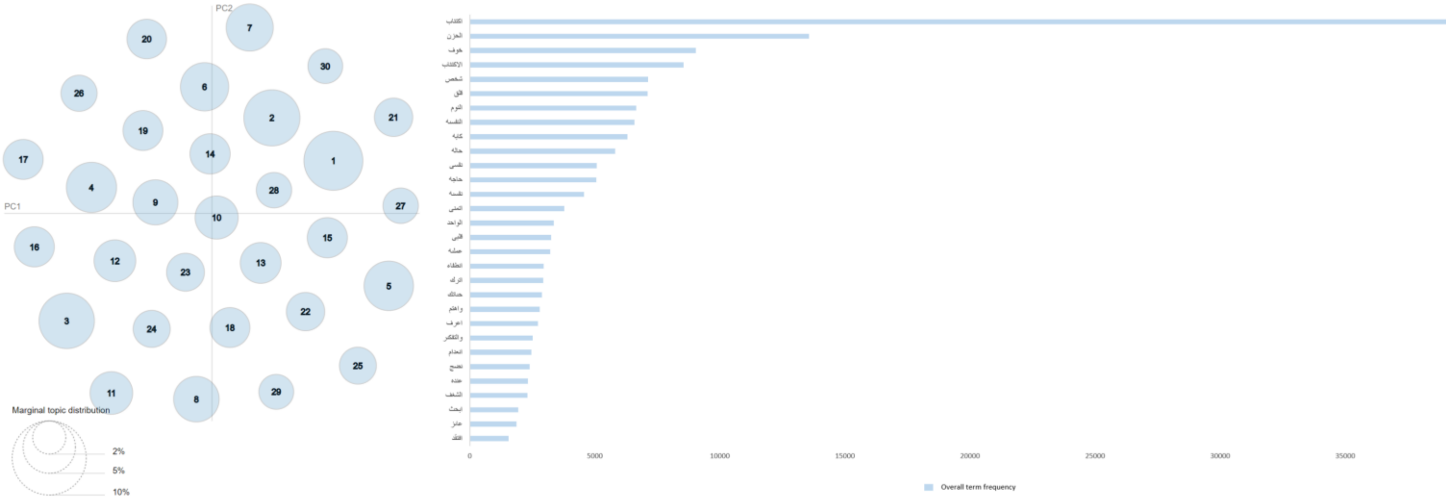

Figure 24. The Intertopic Distance Map of the parameters (Perspective: Causes & Effects)

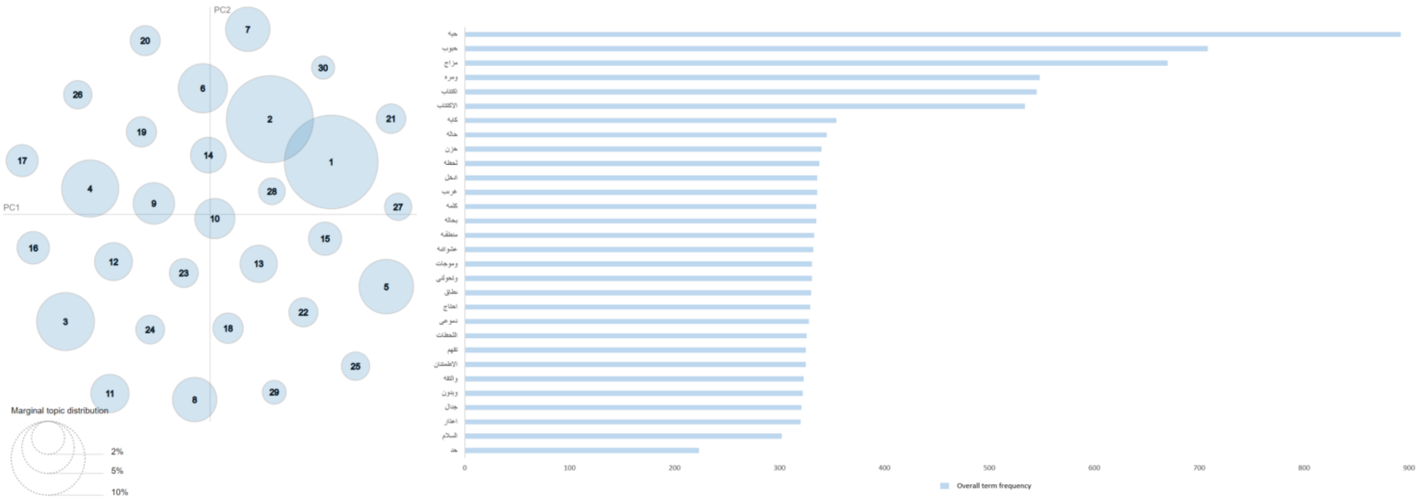

Figure 25. The Intertopic Distance Map of the parameters (Perspective: Drug Abuse)