Exploring Media Portrayals of People with Mental Disorders using NLP

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Abstract: Media plays an important role in creating an impact in society. Several studies show that news media and entertainment channels, at times may create overwhelming images of the mental illness that emphasize criminality and dangerousness. The consequences of such negative impact may impact the audience with stigma and on the other hand, they impair the self-esteem and help-seeking behavior of the people with mental disorders. This is the first study to examine the Singapore media's portrayal of persons with mental disorders (MDs) using text analytics and natural language processing. To date, most studies on media portrayal of people with MDs have been conducted in developed Western countries. This study found that media articles on MDs in Singapore were largely negative in sentiment; even quotes from experts contain aspects of stigma. In addition, crime-related articles on MDs accounted for a significant portion of the corpus. Our model is also extended to detect positive health articles that discuss recovery and motivation. We further developed a stigma classifier based on the machine learning algorithms and text mining techniques. The classifier based on the XGBoosts performed best with an F1-score around 76%.

1 INTRODUCTION

Mental disorders (MDs) affect a significant segment of society. According to a survey by the Institute of Mental Health, one in seven Singaporeans have experienced an MD in their lifetime (Choo, 2020). Despite the prevalence of MDs, the afflicted are still stigmatized: outreach programs have found that persons with MDs in Singapore felt excluded from contributing meaningfully to society and did not feel they could fulfil their personal potential. Media coverage was cited as one major factor contributing to this deep-seated stigma ("Understanding the Quality", 2020).

This study aims to examine Singapore's news portrayal of persons with MDs using text analytics and natural language processing. To date, the bulk of studies on media portrayal of people with mental disorders (MDs) has been conducted in developed countries such as the U.S., U.K., Canada, and Australia. No similar study has been conducted in Singapore, making this the first of its kind. This study makes two contributions to the literature: First, it provides editors and journalists with important principles for creating non-stigmatizing stories about persons with MDs. Second, this study's approach for identifying "aspects of stigma" in news articles can be used by the editorial staff in the newsroom to weed out stigmatizing messages and thus eliminate their negative effects.

1.1 Stigma and MDs

Stigma has been defined as "a social construction that devalues marked members of a community" (Smith, 2007, pp. 235). It involves the categorization of a person into a group based on a distinguishing characteristic or mark (Brown et al., 2003; Dovidio et al., 2003) and results in discrimination, prejudice, or stereotyping (Smith, 2007). As stigmas are shared between members of a community, they impact personal and group interactions (Smith, 2007).

Stigmas and the ensuing negative social attitudes surrounding those suffering from mental disorders (MDs) have been key health and social problem (Corrigan & Penn, 1999). Large portions of

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communities were found to hold highly prejudiced views and hostile attitudes toward these people (Bagley et al., 2005; Dahaf, 1997). These negative attitudes violate the civic rights, self-image, and family life of those afflicted with MDs, and can ultimately interfere with their social integration into the community (Klin & Lemish, 2008). Stigmatization "often results in the creation of laws that (a) identify marks (or stigmata), (b) socially isolate marked groups into geographical locations, and (c) remove the rights of the marked groups and other peoples' obligations to them" (Smith, 2007, p. 235). This process can constrain the stigmatized person's access to health care, employment, education, and housing (Brown et al., 2003; Miller & Major, 2003], which can directly or indirectly impair physical health and even lead to death (Smith, 2007). At its most extreme, the stigmatized may even face eviction from their communities, have their homes set on fire (Wiener et al., 2000), or killed (Gilbert, 2010).

1.2 The Media and Stigma

Content analysis studies have shown that the negative framing of MDs in the media contributes to the public's negative attitudes toward the afflicted (Sieff, 2003). Several studies (Granello & Pauley, 2007; Philo et al., 1994; Thornton & Wahl, 1996; Wahl & Lefkowits, 1989; McGinty et al., 2014; Corrigan et al., 2004; Philo, 1998) reported a relationship between exposure to negative portrayals of those with MDs and negative attitudes toward them, including fear of persons with MD. This relationship is true not only of news stories in newspapers and magazines, but also of fictional stories in soap operas, film, and dramas (Philo, 1998).

Significantly, stigma surrounding persons with MDs has been associated with negative outcomes such as "poor treatment rates, discriminatory housing and employment practices, and public opposition to the expansion of mental health services in local communities" (McGinty et al., 2018, p. 187). A study of U.K. television's depictions of MD argued that the media imagery fuelled the fear of and hostility toward MDs, which in turn significantly affected policies of community care (Rose, 1998).

Nonetheless, longitudinal studies have shown that campaigns can be effective in targeting the stigma surrounding mental illness. For example, researchers found favorable changes in attitudes and challenges to stigma following the 2009 'Time to Change' anti-stigma program (Evans-Lacko, 2013). The number of articles in the UK covering mental illness also saw a substantial increase from 2008 to 2016, with a small but significant positive change in newspaper reporting on mental health topics through an observed increase in anti-stigmatizing articles (Rhydderch et al., 2016).

This study aims to examine Singapore's news portrayal of persons with MDs using text analytics and natural language processing. To date, the bulk of studies on media portrayal of people with mental disorders (MDs) has been conducted in developed countries such as the U.S., U.K., Canada, and Australia. No similar study has been conducted in Singapore, making this the first of its kind. This study makes two contributions to the literature: First, it provides editors and journalists with important principles/methods for creating non-stigmatizing stories about persons with MDs. Second, this study's approach for identifying "aspects of stigma" in news articles can be used by the healthcare staff to act upon when preparing or publishing such articles.

2 MATERIALS & METHODS

We study two text analytics methods to analyse the articles. Firstly, rule-based approach as the news articles should be analysed in a heuristic approach to process human behaviour in discovering stigma in the sentences. Secondly, we propose a machine learning based approach for stigma prediction in news articles. In this section, we present the methodology (data and analysis) followed by the solution models.

2.1 Data Collection

The data collection process requires three components; Sources, data crawling, and article processing.

Data Sources: In consultation with Singapore's National Council of Social Services (NCSS), the scope of the study was narrowed to focus on mental health-related news articles published by the Singapore Press Holdings (SPH) and MediaCorp, Singapore's largest media organizations. Specifically, the study focused on The Straits Times (SPH), The Business Times (SPH) and The New Paper (SPH), Channel NewsAsia (CNA), and Today. To commence data collection, a list of mental health-related terms from a study exploring the portrayal of mental health in Australian newspapers was used (Kenez, 2015). These article search keywords were tweaked to fit the local context (see Table 1).

Crawler: A combination of BeautifulSoup (Richardson, 2007) and Selenium webdriver (Narayanan, 2016) was used to crawl for the articles.

Article Details: As each website had a different interface, three different programs were required to retrieve the following article details; title of the article, body text of the article, author, publisher, published date, and section that the article belongs to

2.2 Data Preparation

Recall that we propose two different approaches for the solution design to detect stigma in the articles. The rule-based approaches are heavily dependent on the dictionaries. Further, in our preliminary analysis, we observed that health-related articles also appear more often with the crime. Therefore, in the data preparation stage, we consider these two observations in our data preparation steps.

Lexicon Preparation: Four dictionaries (Table 1) were prepared to facilitate data cleaning and analysis:

• Stigmatizing phrases: The stigma dictionary includes phrases such as “crazy”, “lunatic”, “commit suicide” and “psycho” (Kenez, 2015).

• Crime phrases: The crime dictionary includes words such as “assault”, “victim”, “threaten”, etc (“Vocabulary University”, 2020). This list aids to separating crime and non-crime articles.

• Medical phrases: The medical dictionary includes words such as “depression”, “depressive”, “phobia”, “phobic”, etc. This list was created from the synonyms of the stigma words using Wordnet (George, 1995).

• Recovery phrases: The recovery dictionary includes words such as “confidence”, “coping”, “determination”, etc (Kenez, 2015).

Data Cleaning: The initial results were extensive but yielded many articles that were not related to mental health. Thus, several filtering steps were undertaken to focus on mental health articles.

1. Article Filtering: Preliminary filtering of articles was done by removing articles found in sections that are not related to mental health. The remaining articles were then ranked on the basis of the number of keyword matches. Articles with fewer than two mental health keyword matches were found not to be related to mental health. These articles either mentioned mental health in passing or were using the term in a different context. These articles were dropped from the corpus. Finally, these articles were manually inspected to ensure that they are related to mental health. After pruning, a final corpus of 1930 articles remained.

Table 1: Keywords used for the data collection and content analysis (Examples).

Addiction Disorder, Behavioural Disorder, Bipolar, Breakdown, Depressed, Depressing, Depression, Depressive, Depressive Disorder, Despair, Distress,…
Article search keywords
Bonkers, Commit Suicide, Craziness, Crazy, Deranged, Freak, Gila, Halfwit, Insane, Loco, Loony, Lunacy, Lunatic, Mad, Madman, Madness, Maniac, Maniac, Mentally Ill, Nutcase, Nuts, Psycho, Psychotic, Siao, Unbalanced,..
Stigma dictionary
Acceptance, Actualisation, Adapt, Adapted, Autonomous, Autonomy, Confidence, Confident, Contentment, Cope, Coping, Determination, Determined, Efficacy, Esteem, Fulfilment, Happiness, Happy, Meditate, Meditation, ..
Recovery or wellness dictionary
anxiety, anxious, anxiousness, bipolar, breakdown, clinical, compulsive, dementia, depress, depressed, depressing, depression, depressive, disorder, dying, headache, hoard, hoarder, hurt, injury, manic, mental, nervous, obsessional,..
Medical dictionary
Abuse, Accomplice, Accused, Accuser, Aggravated assault, Alcohol, Alert, Alias, Alibi, Alienate, Allegation, Ammunition, Appeal, Armed, Arraignment, Arrest, Arsenal, Arson, Art forgery, Assailant, Assault, Attack..
Crime dictionary

2. Article Categorization: In this step, the characteristics of crime versus non-crime articles in the context of mental health reporting were assessed. To do this, a crime dictionary (see Table 1) was used to identify crime articles. A detailed inspection concluded that articles with fewer than three crime keyword matches can be confidently classified as non-crime. However, it was not possible to confidently classify a document having more than three crime keyword matches as being related to crime. Therefore, the rest of the articles had to be manually determined with the aid of the crime dictionary.

2.3 Stigma Analysis Methods

In our study on news articles, the analysis is conducted on both the article-level and quote-level.

1. Article-Level Analysis:

The article-level analysis examined the title, subtitle as well as the first section of each article. Based on feedback from NCSS, journalists put the heaviest effort into crafting these sections of an article. Similarly, readers tend to focus on the title, subtitle, and first section, as their attention spans decline in tandem with the length of the article. Therefore, these elements are extracted from each article.

2. Quote-Level Analysis:

The quote-level analysis examines only the quotes in an article. Each quote in an article is extracted and analyzed on multiple levels. Readers also tend to read short, highlighted quotes as the articles might be lengthy. The quotes are usually placed under the pictures to attract the attention of readers.

3 SOLUTION DESIGN

3.1 Rule-based Solution Model

Figure 1 shows the rule-based solution model used in this study to discover the stigmatizing articles.

A. Text Extraction

In this step, for each article, we extract quotes using python regular expressions such as quotations. The quotes are used for quote analysis. Similarly, for article analysis, we extract the title, sub-title, and first section from the article text. In our preliminary analysis, the first paragraphs mostly summarise the information in the news. Moreover, the audience usually read the first paragraph and the quotations in the news articles.

B. String Phrase Match

In this step, we perform the textual match of the keywords using the stigma dictionary to discover the presence or absence of stigmatizing phrases. We compiled a list of keywords and their associated synonym using Wordnet (George, 1995) These keywords include ‘crazy’, ‘lunatic’, and ‘psycho’.

C. Data Normalization

In sentiment extraction, terms are usually tagged as negative or positive. In the process of obtaining the sentiment scores, the medical terms commonly found in mental health reporting such as depression, panic, and anxiety are judged to be negative by the sentiment lexicon. Therefore, such words are filtered through the use of the medical phrase dictionary.

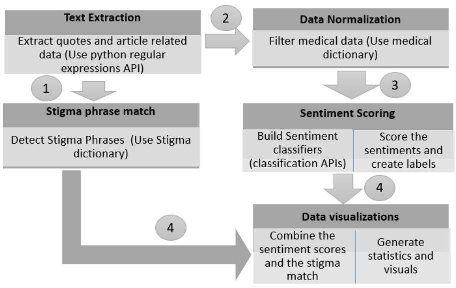


Figure 1: Rule-based Solution Design.

D. Sentiment scoring

Sentiment analysis computationally identifies the writer’s feelings and attitude towards a particular topic – i.e. positive, negative, or neutral. Three types of lexicon-based sentiment analyses are compared: Lexicon based UIC Sentiment Analysis (Liu, 2015), TextBlob Sentiment Analysis (TextBlob, 2020), and Vader Sentiment Analysis (Hutto and Gilbert, 2014).

a) Lexicon: Liu, 2015 compiled a list of words for sentiment detection (Liu, 2015). It consists of around 6,800 positive and negative sentiment words in the English language. An article’s score is the sum of the scores of all its words.

b) TextBlob: This sentiment module has a default implementation, NaiveBayesAnalyzer – an NLTK classifier trained on movie reviews. TextBlob returns 2 values, ‘Polarity’ and “Subjectivity”.

c) VADER: This is a rule-based and lexicon sentiment analysis tool and unlike the typical bag-of-words model, VADER also implements the grammatical and syntactical rules. We consider the compound score to identify the overall sentiment.

E. Data Visualization

Consolidation of the results is achieved by computing the overall outputs from the stigmatizing phrase analysis step and the sentiment analysis step. Both steps help to indicate the presence of stigma in a given text. The Tableau dashboard is used to visualize and analyze the results.

3.2 Machine Learning Model

The machine learning approach for this study attempts to develop a stigma classification model using supervised learning techniques. Ground truth of manually labeled mental health articles will be formulated and be used to train the models. With input from NCSS, a Google Form survey was designed to conduct the labeling process. The survey contains the following questions:

1. Do you think that the title of the article is stigmatizing?

If yes, please identify the words/phrases in the title that are stigmatizing

2. Do you think that the main (body) of the article is stigmatizing?

If yes, please identify sentences in the main article that are stigmatizing. Then identify a few specific words/phrases in the main article that are stigmatizing

3. Is this article crime-related?

If yes, does the article imply that the person's mental health condition caused the crime? If you answered yes to the above question, what are the problematic statements/phrases?

Questions 1 and 2 attempt to identify whether the title or the body of the article is stigmatizing.

Question 3 is only relevant to crime-related articles and attempts to find out if a correlation is made between the mental health condition and crime.

The classifier development process would involve text preprocessing, model training/tuning, and model selection. The best performing model would then be selected based on our selected performance metric, F1-Score and applying cross-validation. In this study, we implemented four classifiers (Christopher, 2006) as described below.

A. Random forest: RF is a classification algorithm that works by forming multiple decision trees at training and testing it outputs the class that is the mode of the classes (classification).

B. Log-regression: Logistic regression (LR) statistical method is used for analyzing the dataset and produces a binary outcome. It is a specific category of regression and it is used in the best way to predict the binary and categorical output. The LR is the fast prediction algorithm.

C. Support vector machines: SVM classifier represents the instances as a set of points of 2 types in N-dimensional space and generates an (N - 1) dimensional hyperplane to separate those points into 2 groups. SVM attempts to find a straight line that separates those points into 2 types and is situated as far as possible from all those points.

D. XGBoosts: XGBoost is a decision-tree-based ensemble machine learning algorithm that uses a gradient boosting framework. It provides a stronger regularization framework that constrains overfitting to overcome this shortcoming. Therefore, it has gained much popularity recently and has become a state-of-the-art machine learning algorithm.

4 EXPERIMENTS

4.1 Rules-based Evaluations

In this section, we first present the results of the evaluation of the steps in the rule-based model.

Table 2: Sentiment classification results.

Model	Precision	Recall	F1-Score	Accuracy
Vader	**0.71**	**0.77**	**0.73**	**0.73**
Textblob	0.59	0.61	0.58	0.63
Lexicon	0.7	0.69	0.58	0.61

As depicted in Table 2, Vader sentiment classifier is the most optimal one in terms of the F1- Score which is the harmonic mean between the recall and the precision. Another curious fact is that positive and neutral labels are effectively separable by Vader unlike the negative variables. This could be because extreme negative keywords indicating the stigma and crime are removed from the data processing stage. From this analysis, we choose Vader as the best tool and continued with the sentiment classification for all the articles.

4.2 Machine Learning Evaluations

We asked the human judges to label 154 articles. Out of 154 articles being labeled, we found that 22% of the title to be stigmatizing. We then combined these titles with the stigmatizing sentence found in the article body and formed the labeled dataset. This dataset consists of a total of 218 sentences and titles, with 99 out of 218 sentences found to be stigmatizing.

For our supervised learning model, we use TFIDF (Term Frequency – Inverse Document Frequency) as features. All the classification models were tested and we used Cross-Validation and F1-Score as performance metrics to evaluate and select the best model. Cross-validation with 5 folds was used because our dataset is small. In this method, the dataset is divided into five folds. Each run, one-fold will act as a validation set and the rest will act as the training set.

F1-Score evaluation metric is selected as our evaluation metric since it considers both the precision and recall of the test to compute the score. We perform parameter tuning on all the models using Random Grid Search with F1 score as our target. The parameters corresponding to the best F1 score were then employed to train our model. Table 3 depicts the model results.

Table 3: Stigma classifier performance.

Model	Precision	Recall	F1-score	accuracy
RF	0.824	0.667	0.737	0.773
LR	0.786	0.524	0.629	0.705
SVM	**0.833**	0.476	0.606	0.705
XGBoost	0.762	**0.762**	**0.762**	**0.772**

XGBoost yielded the best F-Score of 0.762 and it is selected as our machine learning model. Our parameters for the model are as follows; 'subsample': 0.8, 'min_child_weight': 1, 'max_depth': 11, 'gamma': 1. Stigma classifier based on XGBoosts is suitable to predict the stigma on the news articles at the sentence level.

5 INSIGHTS FROM THE DATA

5.1 Exploratory Analysis of Articles

The article statistics are shown in Figure 2. The quarter-to-quarter distribution of mental health-related articles remained fairly consistent throughout the period under study, averaging around 130 articles each quarter. The number of articles peaked in Q3 of 2016 – this can be attributed to an increase in the number of editorials on suicide awareness after the Samaritans of Singapore (SOS) annual report showed that the number of suicide cases in 2016 was the highest in recent years.

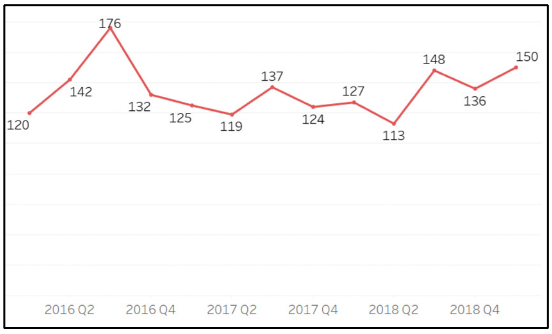


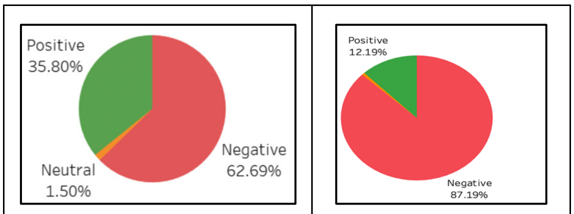
Figure 2: Distribution of articles over the years.

The Straits Times accounted for nearly half the total number of articles produced during the period. The next three publishers, Today Online, Channel NewsAsia, and The New Paper each published roughly the same number of articles. The Business Times had the least number of articles related to mental health, with just 39 articles across the three-year period (see Figure 2b).

5.2 Stigma Analysis in Articles

5.2.1 Sentiment Analysis and Crime Proportion

Articles about crime-related mental health issues made up about 41% of all articles on mental health The overall sentiment of mental health-related articles tends to be negative – negative articles made up more than half of the corpus (see Figure 3).



Distribution of articles by sentiment	Distribution of crime articles by sentiments

Figure 3: Article statistics by types and sentiments.

Of 41% of crime articles, about 88% of articles are negatively polarised. This is expected as the nature of crime words is usually negative. A high proportion of crime articles could influence the public to equate MDs with criminality. In the next sub-sections, we shall study the stigma in the articles.

5.2.2 Stigma Analysis

1. Analysis – Article level

Depression was the most frequently mentioned MD (see Figure 4). According to the World Health Organization, depression is the leading cause of disabilities worldwide and the most common MD in Singapore (“Depression Vocabulary”, 2020), affecting one in sixteen Singaporeans. The next two most common MDs were anxiety and trauma. Hoarding was the least reported MD.

The color coding represents how positively or negatively each MD was portrayed; a negative portrayal is shown in red and a positive portrayal is shown in green. Personality disorder, paranoia and brief psychotic disorder were the most negatively portrayed MD. Hoarding was the only mental condition with a neutral sentiment. “Mentally ill”, “psychotic” and “commit suicide” are the top three frequently used terms to label people. At the article level, we observed 1.5% of titles are stigmatized, 1.55% of sub-titles are stigmatized and 6.6% of first sections are stigmatized. Though the numbers are very low, given the impact of stigma, detecting such articles during the editorial stage is critical.

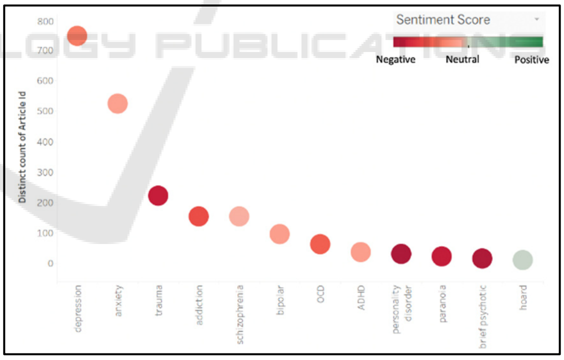


Figure 4: Distribution of the type of mental health condition.

2. Analysis – Quote level

An analysis of the quotes in each article was conducted to determine if the quotes contain stigmatizing elements. The result of a sample quote analysis is shown in Figure 5.

In this example, the word “crazy” in the quote perpetuates the negative stereotype that people with MDs are divorced from reality, irrational, or incapable of making decisions.

Our model extracted 9914 quotes in total and we observed only 20 quotes which are 0.002% of quotes are stigmatized. This indicates that in Singapore's new articles, the stigma is low in terms of the quoted content compare to the article title and first sections.

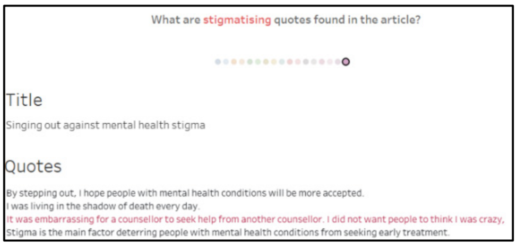


Figure 5: Quote analysis.

5.3 Media Positive Impact Analysis

Articles on wellbeing and recovery help to educate the public about mental health conditions, decrease discrimination towards persons with mental conditions, and encourage help-seeking behavior. To find these articles, keywords from a recovery dictionary were used. In total, these articles made up about 15% of all mental health reports. These articles are more likely to be positive in sentiment and frequently appear in the lifestyle and commentary sections of the media (see Figure 6).

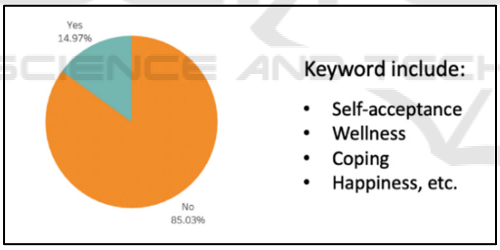


Figure 6: Recovery and wellbeing articles.

6 DISCUSSIONS

This study shows that mental health-related articles in Singapore were primarily negative in sentiment and crime-related articles accounted for a significant portion (40%) of the corpus (see Figure 3). The high proportion of articles associating MDs with crime is troubling, as it may influence the public to equate MDs with danger and violence. To complicate matters, the quotes – including those given by experts – contain stigma aspects. As experts have been rated as the most credible source of information (Edelman, 2020), their words carry disproportionate weight.

As media articles have the potential to promote mental health and contribute to de-stigmatization (Klin & Lemish, 2008), editors can play a more proactive gatekeeping role and counteract the largely negative portrayal of MDs with articles on wellbeing and recovery, which accounted for only 15% of the corpus. In addition, they (and their newsrooms) can use the solution model in this study to identify and weed out stigmatizing elements in their articles about MDs.

There are three limitations to this study. First, although a keyword-based approach was used to filter the articles, it is possible that the keyword list is non-exhaustive. This may have resulted in the unintended exclusion of some mental health articles from the study. Second, only the first section of each article was analyzed for stigma. Future studies can overcome this limitation by applying the model to the entire article text. Finally, our medical dictionary is limited to medical mental illness terms only. There might be other medical terms in the articles which may affect the sentiment scores of the mode. In particular, they may have impacted the negative scoring by the sentiment model. A machine-learning approach can overcome this limitation by training the model with both the stigma and non-stigma datasets.

7 CONCLUSIONS

This study analyzed Singapore media articles to shed light on media stigmatization of MDs in the country. It proposes a rule-based solution model based on text mining and NLP techniques which can automatically identify aspects of stigma in media articles. In addition to flagging stigmatizing articles, the model can identify specific sentences and quotes that are stigmatizing. Such a model can help editors to remove stigmatizing elements before the publication of an article. At the same time, however, it can identify positive articles (e.g. about recovery help and help-seeking behavior). The model's dual advantage can empower editors to address the negative tone that is prevalent in media coverage of MDs. Last, this model can be used to run a course for journalists who cover MDs. Even though this study focused on news articles, the methods of analysis and solution model can be extended to other media, such as social media, blogs, opinion articles, and expert reviews.

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