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Topic Modeling Methods on Alcohol Use Disorder (AUD)-Therapy Text Messages for Emotional Support

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**Abstract:** Alcohol usage can harm health and society for both the drinker and other people. Digital health platforms such as text messaging and mobile therapy are being increasingly embraced by patients as a valuable source of alcohol use disorder treatment. This mobile therapy-generated treatment comes in the form of text messages, and is normally characterized as short text and sparse. Since many real-world text-based data need semantic interpretation to reveal meaningful and relevant latent topics, research in Short Text Topic Modeling (STTM) was conducted. The current study examines the topics included in alcohol use disorder mobile therapy using STTM, particularly from the text messages sent by mental health professionals. First, the best topic modeling technique from STTM needs to be identified for text-based AUD therapy. Then, the current study identifies the topics in the texts of AUD therapy with the help of mental health professionals. Before the main experiment, a pilot study was conducted using ten topic modeling techniques with 28 text messages from alcohol use disorder therapy datasets and different hyperparameter settings. The performance evaluation is conducted on the datasets in terms of several metrics, such as classification accuracy, purity, normalized mutual information, and topic coherence. Based on the performance, Latent Feature Latent Dirichlet Allocation (LFLDA) with α = 0.05, β = 0.01, and K = 14 is found to be the most suitable hyperparameter setting for the alcohol use disorder (AUD) text messages dataset and is used further in the main experiment with 220 sample text. Top 20 words of each topic group resulted from the main experiment were interpreted by mental health professionals in a focus group interview. The findings from the main experiment show that the AUD text messages dataset comprises 14 interpretable topics that are classified under the domain of emotional support such as treatment planning, support and encouragement, coping strategies, self-monitoring, information on consequences, self-efficacy, and lifestyle remedies. These topics and words listed serve as references for mental health professionals when building text messages to discuss a wide range of topics in AUD therapy. This study contributes knowledge on the potentiality of topic modeling analysis in exploring hidden topics inside text messages for AUD therapy as well as revealing the topics used by professionals in AUD treatment. The topic modeling analysis is a useful method for professionals to explore the content of text messages prior to preparation for a therapy.

**Keywords:** Alcohol use disorder topics; text message therapy; therapy topics; topic modeling; mobile therapy

**1 Introduction**

Excessive drinks of alcohol over a single episode are referred to as alcohol misuse. Meanwhile, alcohol use disorder (AUD) occurs when alcohol misuse repeatedly happens over time, and it starts to impact one’s health and life. Reference [1] stated that there is a distinct dose-response association between the amount of alcohol taken and the risk of particular harm for the majority of alcohol-related diseases and injuries. It was estimated that alcohol misuse contributes to 1 in 8 deaths among US individuals aged 20 to 64, including 1 in 5 deaths among people aged 20 to 49 [2]. In 2017, 1.4% of the world’s population suffer from AUD [1]. Impacts are attributable to alcohol, not just for deaths caused by serious illness (cancer-specific mortality and cardiovascular), but also for the quality of life, especially in younger drinkers [3]. As a preventive measure to the problem of AUD, various interventions use digital telecommunication tools to deliver treatment to patients, especially on the emotional part. Text messaging, for example, has been widely used to reduce alcohol cravings, alcohol use, and alcohol-related harm for individuals suffering from AUD [4–7]. However, studies on the topics included in text messaging interventions meant to deliver AUD therapy are still limited. Topics are a crucial component of text messages for AUD therapy. Topics in alcohol therapy that could be mentioned as preferred by patients are supportive/empowering messages, commitment reminders, threatening/consequential messages, and educational messages [8]. Other acceptable topics are practical advice, motivation, and facts such as how alcohol affects sleep. However, different content for text messages should be used due to people having different needs. Information in the treatment topic content that does not focus specifically on the patient's problem was found as a factor that causes withdrawal from treatment [9]. This is also in line with other findings where one of the reasons participants did not continue treatment was that they received messages that were no longer useful to them [10]. Therefore, there is an advantage in knowing the suitable content for text messages to be used in AUD therapy, which will be beneficial to both therapists and patients.

Short text messages used in AUD therapy also have a significant drawback in that the analysis of the content requires a high processing workload. The standard approach necessitates analysts to read and manually classify all or a portion of text messages to discover the subjects discussed in the therapy [11]. A manual method like this takes a long time and is prone to mistakes, especially when several researchers are analyzing the responses independently. Some scholars suggest a few techniques to analyze short text messages using topic modeling methods [12–17]. Topic modeling is a generative model used in machine learning that offers a probabilistic framework for the frequency of occurrence of words in documents from a corpus. The goal of topic modeling is to identify the latent distributions underlying a set of observational data, such as word distribution in a collection of documents. When it comes to topic modeling, the word order information is ignored, and only the frequency of words is used as a guide to model a topic. This is also referred to as the word exchange assumption in a document, and this assumption leads to a bag-of-words model [18]. For finding the statistical patterns concealed in textual data in supervised, semi-supervised, and unsupervised environments, topic modeling is particularly helpful in the context of natural language processing. Topic modeling has been used to discover latent topics that are hidden within a collection of texts, including emails, documents, short texts, tweets, and posts on Facebook and Twitter [19]. For example, Latent Dirichlet Allocation (LDA) and a set of topic models in R were used to find themes in user discussions on TeenHelp.org that were associated with self-injurious thoughts and behavior (SITB) [20]. Other than that, latent topics and the frequency of phrases associated with depression that was collected from posts on Reddit sites were analyzed using LDA [21]. However, short-text sparsity issues make long-text topic modeling, like LDA, less effective in identifying latent topics. For this problem, scholars introduced various improvised topic modeling techniques that are more applicable to short texts [22] and [23]. Results from each topic modeling did not agree with one another when different data sources were used and even if the same choice of K or other parameter settings were applied [24] and [25]. Moreover, different topic models are appropriate for various application contexts and data properties [26]. Therefore, selecting the most appropriate topic model is an important key to conducting a good topic inference. Our goal goes beyond testing the ten-topic modeling on text messages used for AUD therapy in that we study the topics contained in them. First, the best topic modeling technique needs to be identified for text-based AUD therapy. Then, the current study identifies the topics in the texts of AUD therapy with the help of mental health professionals.

**2 Topic Modeling Applications**

In topic modeling, documents are weighted mixtures of discrete topics, in which each discrete topic is just a probability distribution over all the words, and words make up documents. The process of inferring a topic model yields statistical data on the frequency of the topic, and the vocabulary used to convey each topic [27]. Latent Dirichlet Allocation (LDA) is the earliest topic modeling introduced, and it has several advantages over manual coding. A large number of documents that would be too expensive to code manually can be processed by LDA [28]. LDA offers a trustworthy and reproducible topic classification. Both of these aspects are not possible with manual coding, which is dependent on the subjective assessment of the human coders. For the underlying taxonomy of categories, LDA does not require researchers to provide any rules or keywords in advance. By fitting the presumptive statistical model to the full textual corpus, LDA can identify topics and their probabilistic relationships with keywords. To categorize issues using a manual coding system or dictionary, however, researchers must first provide a deterministic set of rules or keywords. It is nearly impossible to predict the topic in advance by going through keywords manually across all textual corpus during the analysis. However, LDA has weaknesses in dealing with a short text [29], and this leads to much research being devoted to improvising LDA topic modeling [16]. Short texts are aggregated for data sparsity using a self-aggregated topic model (SATM). But as the size of the data expands, the number of parameters does as well, making it computationally expensive and prone to overfitting. Therefore, Pseudo-Document-Based Topic Modeling (PTM) based on pseudo-documents for short texts was suggested [16]. PTM automatically aggregates short texts similarly to SATM, but it limits each pseudo document to only having one topic, which reduces the amount of time needed for text aggregation. Reference [15] offers a Biterm Topic Model (BTM) that focuses on modeling unordered word pairs (biterms) across the corpus in the interim. BTM produces topic representations that are more discriminating and cohesive [30]. To derive topic distributions as a classification feature, BTM utilizes a superior inference procedure. Due to this, BTM nevertheless achieves great accuracy even though its biterms lack discrimination. Both semantic and syntactic information are encoded by word embedding. In vector space, similar words are close together. In contrast to the aggregation strategy, the entire corpus is considered rather than just the distribution of topics across the corpus [30]. Then, using a combination of the Dirichlet multinominal model (DMM) component and the word embedding component, Latent Feature Dirichlet Multinomial Mixture (LFDMM) draws the topic-word multinominal distribution [14]. With the embedding component, topics are projected into the same vector space as word embeddings. The use of LF-DMM is constrained by the computationally expensive nature of such projections [30]. Then, a Generalized Polya urn (GPU) was added to extend DMM [13]. The GPU uses word embeddings to encourage semantically related terms under similar topics, creating more cohesive and relevant results. Reference [29] went on further to extend DMM with a Poisson distribution (PDMM), allowing each short text to have one to three linked subjects instead of only one. Generalized Polya urn Poisson-based Dirichlet Multinomial Mixture Model (GPUPDMM) has good performance, but because of the Gibbs sampling technique, it has a high time complexity [30].

The topic exploration of short text messages is carried out based on several topic modeling techniques. Topic modeling has been applied to extract topics from various kinds of corpora, including microblogs [31]**,** free-text feedback in healthcare [32], tweeter posts on the development ofsocial enterprise [33], online forums discussion on self-injurious thoughts and behaviors [20] and more. Reference [31] presented work using LDA to explore public responses to Coronavirus disease 2019 (COVID-19). As an alternative to a traditional survey, the study collected public text posts on social media called Weibo. LDA analysis of people’s texts related to the COVID-19 outbreak has found significant topics, namely facts about COVID-19, people expressing support for frontline workers, encouraging each other spiritually, showing concerns about economics, and suggesting ways for life restoration. Reference [34] looked into the topic of research trends using LDA-based topic modeling to predict what technology will be invented in the future. Reference [33] studied the development of social enterprises on tweeter posts using LDA. Although LDA found three topics to best represent the tweeter posts, the study added another topic (“people”) due to the word “people” frequently appearing in all topics. This is found to be relevant because people have a strong relationship in the social enterprise context. Reference [35] uses an unsupervised learning method, namely LDA topic modeling, for extracting topics from written student responses. The study is interested in finding topics on teaching behavior in open-ended surveys answered by a large scale of students. The findings of the study show that eight topics of teaching domains were discovered and suggest that the relation between topic modeling and human analysis is complementary. Another study [11] compares the performance of LDA, LFLDA, BTM and Word Network Topic Modeling (WNTM) on open-ended responses about the recommendation for developing software on a certain platform. Although BTM and WNTM results were promising, further research is still needed to show the practicality of topic modeling in replacing the human coder. Reference [25] conducted experiments on texts from six different sources using nine short text topic modeling techniques. Their findings reveal that each short text topic modeling produced different results for each dataset in the experiment. This indicates that short-text topic modeling is dataset-dependent. Recently created advanced topic modeling like DMM, BTM, PTM, WNTM, and SATM are not being widely employed because of their limited visibility or lack of exposure. When compared to the conventional models, they do appear to perform better [36]. Hence, the current study conducts experiments using these advanced topic modeling.

**3 Methodology**

***3.1 Experimental Design***

Several experiments were conducted on the sample of text messages used in alcohol use disorder therapy. The experiments were conducted on a Windows 10 Pro with Intel(R) Core (TM) i5-6200U CPU and 8GB RAM. To begin with, a pilot study was conducted to examine the best-performing topic modeling in classifying AUD text messages into different topics. The pilot study involved experiments on ten topic modelings, namely Latent Dirichlet Allocation (LDA), Biterm Topic Modeling (BTM), Pseudo-Document-Based Topic Modeling (PTM), Self-aggregation Topic Modeling (SATM), Word Network Topic Model (WNTM), Latent Feature Latent Dirichlet Allocation (LFLDA), Latent Feature Dirichlet Multinomial Mixture (LFDMM), Gibbs Sampling Dirichlet Multinomial Mixture (GSDMM), Generalized Polya urn Dirichlet Multinomial Mixture (GPUDMM) and Generalized Polya urn Poisson-based Dirichlet Multinomial Mixture Model (GPUPDMM). In the pilot study, 28 text messages of AUD therapy were used for the modeling algorithms to extract the hidden topics contained in them. The algorithms need a set of hyperparameters to execute the task which is explained in the next section. Next, the best-performing topic modeling and the ideal combination of hyperparameters are identified from the pilot study. The chosen topic modeling and hyperparameters are used in the main experiment for further analysis. In the main experiment, the present study applied 220 text messages of AUD therapy to run an experiment using the chosen topic modeling and hyperparameters. At this stage, the experiment particularly focuses on the words classified into several topic groups by the algorithms. Finally, the list of topics that was produced from the main experiment is presented to a group of mental health professionals in a small focus group interview. The purpose of the interview is to make topic labeling by analyzing the top 20 words in each topic group. Each topic group is given a label based on consensus expressed by the mental health professionals. The data source and parameter settings are presented in the following section.…

***3.2 Data Source***

This study focuses on text messages used by mental health professionals in treating alcohol use disorder, where the treatment targets different types of primary and secondary outcomes. The dataset was developed by collecting text messages used by mental health professionals in alcohol use disorder therapy from previous literature. The text messages were collected from published studies between 2011 and 2021 [4], [5], [8], and [37–47]. As mentioned before, the dataset for the pilot study consists of 28 text messages, whereas the main experiment included 220 text messages. Before the pilot study can be conducted, the number of topics (value of K) must be established. Particularly, a larger number of topics may result in model overfitting; thus, it is important to be cautious while choosing the number of topics for training the model [31]. The selection of the number of topics can be made by carefully and qualitatively examining text message content. A mental health professional was involved in this process. Her expertise in the context of mental health therapy will determine how text messages should be interpreted and labeled with a topic. During the process, most of the text messages are interpreted to only one label. Some text messages, however, are interpreted to have several labels and share the same label with other text messages. Overall, the results indicate that there are nine labels for the AUD therapy text messages dataset. Next, the dataset underwent pre-processing operations in which stop words and numerals were removed, all text is converted to lowercase, and lemmatization was performed. This resulted in 260 words in the pilot study corpus and 1280 words in the main experiment corpus.

***3.3 Parameter Settings***

All ten short text topic modeling techniques are trained using the open-source Short Text Topic Modeling (STTM) with a Java-based library [25]. For each method, past literature was reviewed to select the hyperparameter values. The pre-distribution of the weights of topics in each document is controlled by the parameter alpha, whereas the pre-distribution of the weights of words in each topic is controlled by the value beta. In contrast to low alpha, which indicates that a document is more likely to be represented by a smaller number of topics, high alpha indicates that each document is likely to have a mixture of most of the topics [34]. A low beta indicates that the topic may only have a small number of words, whereas a high beta indicates that each topic is likely to contain a mixture of the majority of the words, not just any word particularly [34]. References [48] and [49] used smaller α values (α = 0.05) within the LDA experiments, whereas other studies used α = 0.1 [14] and [50]. The value of α = 0.1 was also used in the parameter setting for WNTM, GSDMM, LFDMM, and PTM [14], [16], [17], and [25]. It was also discovered that BTM, DMM, and SATM worked well when α = 50/K [13], [25], and [48]. Furthermore, when applied to short texts, several research studies also employed a smaller value of β = 0.01 [14], [15], [25], [48], [50], and [51]. Based on these pieces of literature, it is assumed that smaller values of hyperparameter settings are appropriate for short texts, where the smaller value of β is related to topic word-sparseness, while the smaller value of α implies that short text texts contain less topic [11]. However, other studies also used β = 0.1 for WNTM, GSDMM, and SATM [17], and [25]. The current study conducts experiments on text messages for AUD therapy which is a short text. Thus, two values for each of the hyperparameters α = (0.05, 0.1) and β = (0.01, 0.1) are used, as guided by the previous literature mentioned above.

Each document is treated as one window in BTM, whereas for WNTM, the window size is set to 10 words. All topic modeling methods were run for 2000 iterations. For LFLDA and LFDMM with λ = 0.6, the iteration baseline model was run 1500 times, with further 500 iterations, as stated in the original paper [14]. The word embedding-based topic modeling GPUDMM has additional parameters which set threshold = 0.5, weight = 0.1, filter size = 10, whereas GPUPDMM with λ =1.5, threshold = 0.1, filter size = 10. GPUDMM, GPUPDMM, and LFDMM were trained using pre-trained word embeddings (“glove.6B.300d.txt”), where the dimension of the vector is 300. In addition, the number of topics (K) ranged from 5 to 20, with a step size of 3 being set. This variation K = (5,8,11,14,17,20) is used to observe how topic modeling performs when K is large or small. The range for K was selected based on the number of labels resulting from the manual topic labeling task, with the minimum value of K being five, which is very close to the original number of labels (nine). Considering the significant differences observed between the considerable K values and the ability of the researcher to assess the topic manually, the maximum value of the topic for this experiment is 20. The step size of three was chosen because each document has at least one label and three labels at the most. The best-performing topic model as regards combinations of hyperparameters and the number of topics will be used in the main experiment. The ten topic modeling used in this work are referred to as methods in the text below, whereas model refers to each fitted method with values of α, β, and K.

***3.4 Data Analysis***

To measure the performance of topic modeling quantitatively, past research had used text processing algorithms to evaluate clustering, coherence, prediction score, and classification accuracy [11], [14], [25], and [52]. In addition to that, the outcome generated by the model can be utilized to label the topic group by using human coding [53]. Both quantitative and qualitative methods are applied in this study. The performance measurement is used in the pilot study to determine the best performs topic modeling with combinations of hyperparameters and K values. On the other hand, the topic labeling task is done in the main experiment.

*3.4.1 Performance Measurement*

For the quantitative measurement, the STTM package's document classification accuracy, clustering, and coherence were used in topical document evaluation. First, the distribution of document topics and the performance of each topic modeling method are measured using classification accuracy. Ideally, the document-topic distribution *p (z | d)* is used to assign each document (in this instance, a text message) to the topic that has the highest probability. The STTM package made use of a library for large-scale linear classification (LIBLINEAR) (https://liblinear.bwaldvogel.de/) linear kernel Support Vector Machine (SVM) classifier's default settings. The dataset was subjected to fivefold cross-validation to measure classification accuracy. A higher accuracy shows that the model is more capable of differentiating the learned topic. It also implies that the learned topics are more closely matched to the topics of the actual dataset. Another crucial assessment that measures a topic model's efficacy directly and without external influence is clustering [15] Each topic is regarded as a cluster in document clustering. The topic (z) with the highest probability, *p (z | d)*, was given to each document (d) following the topic probability calculation. Purity and Normalized Mutual Information (NMI) are the two most used clustering measures, which are also used in the current study. Good clustering is shown by a value near 1, whereas bad clustering is near 0. Another evaluation is executed to measure the quality of topic-word distribution, which is referred to as coherence evaluation. The idea behind a coherence score is that words related to the same topic will frequently coexist in a document. It should be noted that the coherence score only accurately assesses frequently occurring terms in a document. This is due to the fact that the less common word used to determine the topic-word distribution is unreliable [15]. In this experiment, the topic coherence score was calculated using one Wikipedia meta-document. A 10-word sliding window was used to determine the Point-Wise Mutual Information (PMI) of each word pair, taking into account the word co-occurrence over the complete dataset of Wikipedia articles.

*3.4.2 Topic Labeling*

Topic labeling is conducted based on the results from the main experiment. From a qualitative standpoint, each topic's words extracted from the main experiment were manually analyzed to understand their meaning and to assign a topic label carefully. Those words are the top 20 most probable words in a topic. The purpose of the labeling is to summarize the content of each topic [35]. Thus, the current study used labels to identify the topics contained in the AUD text messaging therapy. A group of seven mental health professionals who have more than five years of experience in mental health counseling was invited through email to take part in the topic labeling. Upon agreeing, a consent form was filled out by every mental health professional. The process and discussion on topic labeling were conducted online and lasted for two hours. Three steps were used for topic labeling; firstly, mental health professionals analyzed each word in the cluster independently to reveal similarities and associations between words. The semantic features of the words were used to help them describe each associated word during the analysis. Next, mental health professionals interpreted the associated words in the cluster independently by giving a relevant topic label that reflects the meaning of the content. The most representative words were given more weight during topic labeling. Lastly, mental health professionals discuss each topic label suggested with each other in order to come to an agreement

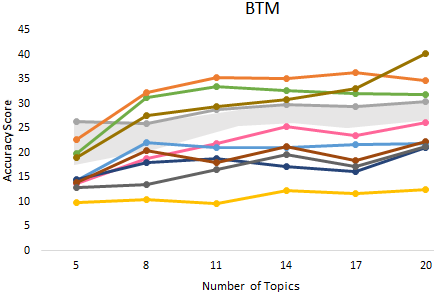
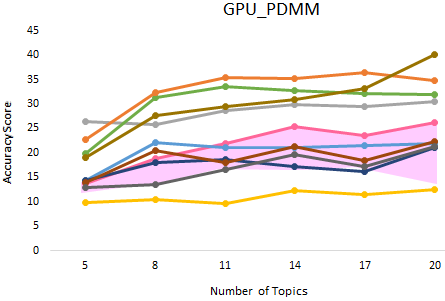
**4 Findings and Discussion**

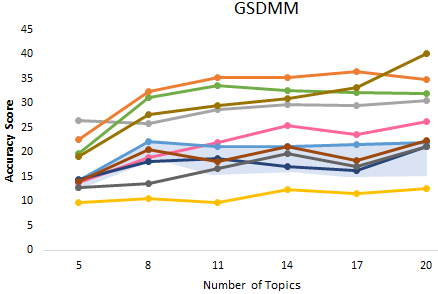
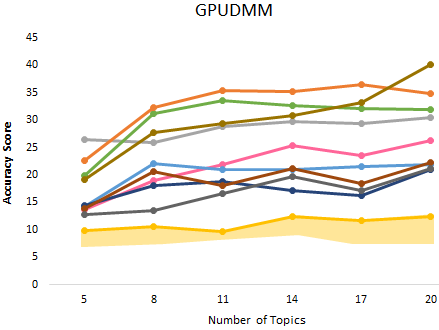
***4.1 Pilot Study***

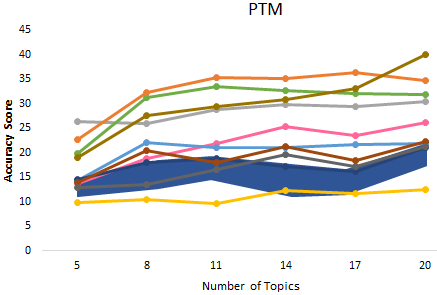
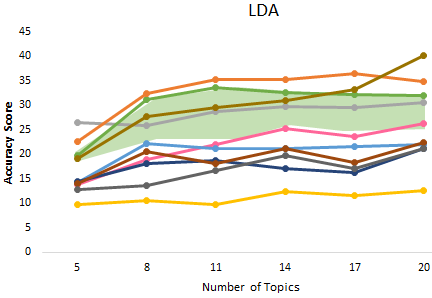
For each topic modeling method, 24 models were run 20 times. Then, the average performance of each model is calculated. This section reports the average performance measures of classification accuracy, clustering, and topic coherence based on the experiment conducted in the pilot study.

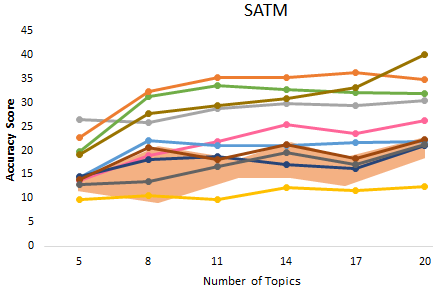
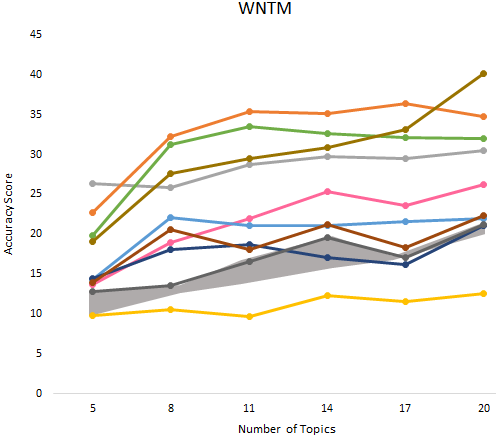
*4.1.1 Classification Accuracy*

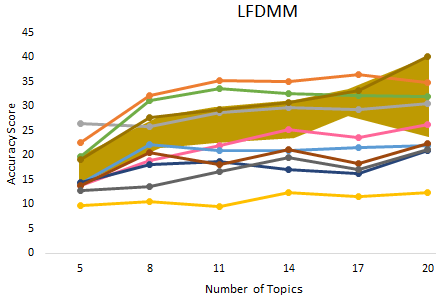
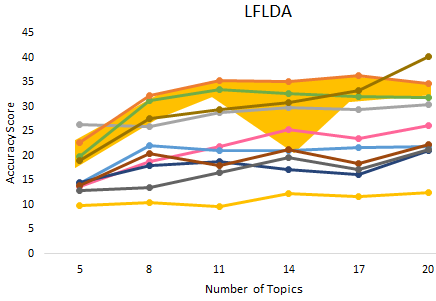
The highest average accuracy scores of each topic modeling method across six different topics are shown in Fig.1. According to Fig. 1, the lines show the best average accuracy score produced by each method. The shaded area under each line indicates the ranges of accuracy scores with different hyperparameter settings applied to the method. The higher boundary indicates the highest score achieved by a method, and the lower boundary indicates the lowest one. LFLDA had the highest score compared to the other topic modeling methods for all K values except when K = 20. In contrast, GPUDMM performs the worst in accuracy evaluation with AUD therapy text messages. Despite the fact that BTM and WNTM are both word co-occurrence methods, the superiority of BTM may be due to the input type used, which is a whole corpus, whereas WNTM produces document-topic distribution learned from pseudo-document. Findings from other pieces of literature also discovered that BTM accomplished far better classification precision than WNTM [25] and [49]. In contrast, others reported that WNTM performed better than BTM in classification precision [11] and [54]. Based on these points, it is worth noting that different topic modeling performs differently depending on the dataset. The notable gap between the upper and lower boundaries of the shaded area in LFLDA indicates that the accuracy of this method is influenced by the hyperparameter setting. Other than that, LDA and LFDMM are among the methods that score high in accuracy evaluation, in which LFDMM outperformed LFLDA when K = 20. Although LDA scores higher than LFDMM in most of the K values, LFDMM performs more consistently in accuracy with increasing K, whereas LDA accuracy performance decreases when K > 11. Moreover, the shaded area in the figures shows that most of the methods are not hyperparameter setting dependent. However, the accuracy of the LFLDA method indicates that it is hyperparameter dependent, especially when K is between 11 to 17. Besides LFLDA, LFDMM and LDA also show dependency on the hyperparameter setting. Hence, the suitable combination of hyperparameter settings must be determined, and to do that, the number of topics must first be identified from the coherence evaluation result.











**Figure 1**: Classification accuracy of ten topic modeling with different values of K.

*4.1.2 Clustering*

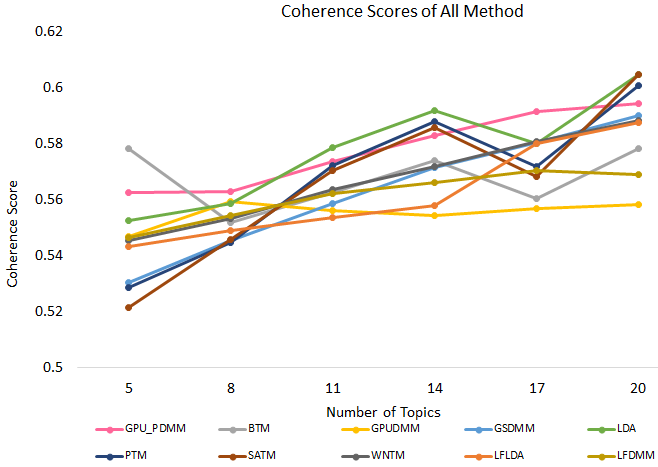
One of the most crucial components of short text topic modeling is clustering, which helps in identifying patterns in the dataset. Fig. 2 presents the results of the clustering evaluation in the form of a line graph, which includes the average purity and NMI scores for each topic modeling. Purity and NMI ratings range from 0 to 1, and the closer they are to 1, the more effectively they cluster data [14]. Overall, for each method, upward trends with an increasing number of topics were produced. It can be observed that LFLDA and LFDMM achieved the highest clustering score and performed consistently with an increase of K. Although LDA outperformed LFDMM in clustering evaluation for some values of K, the performance was inconsistent when K > 11. Moreover, BTM, SATM, and PTM also produce the same pattern as LDA. Working with the AUD dataset, GPUDMM also performs the worst in clustering evaluation. This again shows that GPUDMM is not as good at labeling the sample text messages into its cluster when compared to the golden label. Besides GPUDMM, the differences in scores of Purity and NMI amongst the remaining models are comparatively small, especially when K < 14. In summary, it can be seen that LFLDA, LFDMM, WNTM, and GSDMM perform consistently in clustering evaluation. However, WNTM and GSDMM did not do well in accuracy evaluations. Compared to LFLDA and LFDMM, WNTM and GSDMM also achieve lower scores in accuracy and clustering evaluations. Although LFLDA did not outperform LFDMM for every number of topics in clustering evaluation, LFLDA has at least outweighed LFDMM in four K values. In addition, LFLDA also outweighed LFDMM in accuracy evaluation for five K values.



**Figure 2:** Clustering score of three models with different values of K.

*4.1.3 Topic Coherence*

Topic coherence evaluates the quality of topic-word association by measuring how well the word is assigned to a topic [14] and [25]. The coherence score of all methods for the alcohol dataset is shown in Fig. 3. Overall, all scores show an upward trend, with most of the coherence values increasing with the number of topics. Although LDA, PTM, and SATM show upward trends, the scores decreased when K = 17. GPUPDMM scores better than LDA for some values of K, and so did LDA. The inconsistency of GPUPDMM and LDA performance in coherence evaluation makes it difficult to determine which method is better than the other. In contrast, four methods (WNTM, GSDMM, LFLDA, and LFDMM) perform consistently with an upward trend across the number of topics without any decrement. An interesting aspect to observe from this trend is that it is possible that each alcohol text message may contain more relevant topics. This is due to the fact that people with AUD experience depression and anxiety at the same time [55–57]. Thus, it is not a surprise if a text message for AUD treatment contains more than one topic. Other than that, it can be seen that BTM has the most inconsistent coherence scores, whereas GPUDMM scores the lowest when K > 11. The coherence scores of all methods keep on increasing as the number of topics increases; however, the coherence scores for some methods show a reduction when K = 17. This indicates that all methods could draw more coherence topics when K < 17. There is a possibility that alcohol text messages contain more topics; thus, K = 14 is assumed to be the most suitable number of topics for the text-based AUD therapy dataset.



**Figure 3:** Average performance measure of coherence score of ten models with different values of K.

In summary, GSDMM and LDA scored higher than the rest of the methods in coherence evaluation for most values of K, but GSDMM did not do well in accuracy and clustering evaluations. Meanwhile, LDA scores lower than LFLDA in accuracy evaluation and performs inconsistently in clustering evaluation. Moreover, LDA suffers from topic imbalance, which often causes the inability to identify rare topics [11] and has weaknesses in dealing with a short text [15] and [29]. LFLDA and LFDMM are among the methods that performed higher in accuracy and clustering evaluations than the remaining models for the alcohol dataset. LFLDA not only outperformed LFDMM in clustering evaluation, but it also scored higher than LFDMM in most values of K in accuracy evaluation. This could be due to LFDMM increased noise interference due to the dependence only on external word expansions. LFDMM utilizes word embeddings show lower scores on AUD datasets compared to LFLDA. This is because AUD text message therapy is a domain-specific dataset and word embeddings used in this paper are trained in general datasets. If the experiment of LFDMM is run with re-training word embeddings on domain-specific datasets, the performance could be improved.

Apart from the upward trend in coherence scores, all methods’ coherence scores were close to each other when K = 8. These indicate that the higher the number of topics, the more meaningful topics can be drawn by these models. Other than that, six methods increasingly scored from the other methods when K increased, whereas four methods decreased their scores when K =17. This shows that all methods are able to draw coherent topics when K < 17, whereas some methods found that less coherent topics were drawn when K reaches 17. Therefore, K = 14 will be considered the best number of topics for sample data of AUD text messages in this study. Table 1 shows scores of accuracy, clustering, and coherence of LFLDA with different combinations of hyperparameter settings when K =14. There is an advantage in knowing which hyperparameter setting is the most suitable for the alcohol dataset when K = 14. To achieve this, the highest scores of accuracy, clustering and coherence of LFLDA with K = 14 are chosen. Based on the analysis, LFLDA with α = 0.05, β = 0.01, and K = 14 is found to be the most suitable hyperparameter setting for the AUD text messages dataset. Topic modeling of LFLDA with the chosen hyperparameter setting and K value is used in the main experiment explained in the next section.

**Table 1:** Average performance measures of classification of accuracy, clustering, and coherence of LFLDA when K = 14.

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Hyperparameter Settings** | | | **Performance Evaluations** | | | |
| **alpha** | **beta** | **K** | **Accuracy** | **Clustering** | | **Coherence** |
| **Purity** | **NMI** |
| 0.05 | 0.01 | 14 | 35.17857 | 0.705357 | 0.705492 | 0.553937 |
| 0.05 | 0.1 | 14 | 20.00000 | 0.705357 | 0.701419 | 0.546666 |
| 0.1 | 0.01 | 14 | 31.60714 | 0.691071 | 0.696288 | 0.543015 |
| 0.1 | 0.1 | 14 | 31.25000 | 0.696429 | 0.696657 | 0.538109 |

***4.2 Main Experiment***

As explained in the previous section, the best topic modeling technique is selected based on classification, clustering, and coherence performance. The performance is influenced by the hyperparameter value set during the pilot study. Apart from the selection of the best topic modeling technique, the pilot study also determines the ideal values for alpha, beta, and K to be used in this experiment. The main experiment is conducted using 220 text message samples, and an LFLDA topic modeling technique with α = 0.05, β = 0.01, and K = 14. The results of the main experiment are analyzed to give a label to each topic. Different from the pilot study, the aim of the main experiment is to determine the topics contained in text messages for the therapy of AUD. The result of the main experiment that is of interest is the 20 words that are listed as outputs in each of the 14 topics that have a high probability for a topic group. The words are displayed in Table 2 according to their respective topic groups before being manually analyzed using a qualitative approach.

This section reports the interpretability of the topics using a qualitative approach that involves a group of seven mental health professionals. As discussed in the previous section, the topic modeling method used for topic interpretation is LFLDA with the K = 14. Initially, mental health professionals were presented with a list of 14 topics, where each topic has the top 20 words ordered by word probability. The words are arranged in descending order, with the highest probability to the lowest probability of being generated by the topic. Some words appear in more than one topic, whereas only a few words are unique to one topic, such as “share”, “stick”, “difficult”, “arrange”, “walk”, and “path”, being unique to topic 12. In a 2-hour online interview, the mental health professionals discussed and shared their thoughts on the words presented in each topic for interpretation and topic labeling. The interpretations were conducted by analyzing the top 20 words. They also recall and relate frequent words that they had always used in AUD text-based therapy to help them interpret the words. In addition, they relate common words with the psychotherapy component they have been using. During the discussion, two to three labels were proposed, with the most representative words presented together to provide a clearer justification. Some of the words did not fit any of the topic labels that they suggested. Hence, those words are considered as being less relevant to the topic label. Next, the most suitable topic label is selected after considering the most reasonable thoughts and meaningful and relevant words found in each topic list. Table 2 shows the 14 topics with their respective labeling. For instance, the first topic is labeled as “Plan on alcohol reduction intake to reduce harm” after considering most representative words such as “alcohol,” “drink,” “plan,” “cut,” “help,” “consider,” “day,” “alternate,” “consume,” “free,” “follow,” “monitor,” “sip,” “small” “minimize” and “harm.”

**Table 2:** Topics in text messages for depression therapy produced by LFLDA.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Topic** | **Label** | **Top 20 Words** | |  |
|  | Plan on alcohol reduction intake to reduce harm | alcohol drink plan cut help consider day alternate consume free drinks follow monitor reply sip small rule minimize choice harm | |  |
|  | Set a treatment plan for a patient   * Goal * Appointment * Medication | achieve try give close future appointment patience happen keep take goal medication aim set next away home attend up go | |  |
|  | Dealing with cravings | people activity alcohol care crave recover time involve energy week take hurt process trigger vital destination avoid community down places | |  |
|  | Self-empowerment | power success remember strong enjoy face tempt drink remind fail test responsible decision learn return consequence reward dwell thought recall | |  |
|  | Dealing with lapses | drink think change make bad day week regret application good feel encourage fresh last tab decide easy start worry again | |  |
|  | Maintaining sober state | great keep reduce mind life answer alcohol advice will healthy week text reason news habit tip provide rest quit month | |  |
|  | Relapse prevention | stay control trouble goal decision away place help keep aim positive set slip focus harder stop life pub count active | |  |
|  | Managing financial | remember care health stop money chose open do think accept appointment decide save matter feel way past next tell spend | |  |
|  | Consequences | alcohol avoid depression hangover cause weight tomorrow pros cons list cancer disease drink injury adopt strategy develop much deaths weekday | |  |
|  | Drinking limits (measurement, advice etc.) | drink mililitter goal max reduce wine week spirits beer limit day set safe premix recommend injury consider risk ten half | |  |
|  | Dealing with struggle | urge let get consequence distract consider through interest control pass resist well do know others drive diary fight hear complete | |  |
|  | Planning for safety | plan share friend drive stick designate difficult arrange walk path exception joy tough sign situation safe taxi cash time recover | |  |
|  | Life style remedies | think future choice life clean smart sober live work take thing stay charge like solution power hope dead sacrifice opportunity | |  |
|  | Coping and support system | | support alcohol family friend doctor helpline free problem contact confidential drink forget tell friends forgive provide join feel give encourage | |

For the first topic, the mental health professionals stated the association of the listed words with alcohol reduction strategies. All 20 words were seen to have a strong association with alcohol consumption planning. Through discussion, it can be known that AUD patients will not be able to stop consuming alcohol immediately; instead, the behavior change happens gradually. Therefore, planning a strategy to reduce alcohol intake is one of the topics taught to patients during therapy. It is also understandable that it is difficult for patients to achieve a completely alcohol-free day. Hence, the therapy carried out is to reduce alcohol intake to reduce harm. As a result of discussions, a consensus was reached where all the mental health professionals agreed that "Plan on alcohol reduction intake to reduce harm" was used to represent the content of the first topic. This topic labeling is in line with treatment guidelines mentioned by previous scholars [7], [47], and [58], whose topic plan involves establishing a goal to change drinking behavior and giving brief counseling or simple advice on drinking limits to reduce the risk of harm.

The discussion continued with naming the second topic. Mental health professionals think that the words listed are more representative of the early stages of treatment. This includes setting treatment goals, identifying current levels of achievement, and planning a treatment plan. Through the discussion, the mental health professionals mentioned that usually, the initial stage of the meeting session is when the therapists meet the patient and make an assessment. After the assessment, therapists continue the session by talking about the treatment plan and identifying whether the patient needs medication or regular close monitoring, such as coming for each appointment, individualized treatment for the patients (safety-related needs, concomitant medical conditions, personal background, relationships, life circumstances, and strengths and vulnerabilities), or to set the next appointment at the end of every session. As a result, the phrase "set a treatment plan for a patient" was formed. Then, it was refined by including the words, "goal", "appointment", and "medicine". This is agreed upon by all other experts.

For the third topic, the discussion delves into the words “crave”, “recovery”, and “activity”, which are seen to be linked to actions that need to be taken during the recovery process. For example, how do patients actually think about what needs to be done to prevent relapse? First, identify the trigger that causes the craving, because the craving will cause them to relapse into using. In order to avoid repeated alcohol consumption, patients are taught how to identify triggers for cravings and how to control cravings [59]. This is because the feeling of greed will lead to repetition. Among the triggers are results from an activity or certain situations. For instance, daily occurrences of emotional reactions can easily cause them to drink. Learning how to handle these emotions is essential [60]. In summary, the words in this topic group are related to relapse and craving. Therefore, the third topic is labeled “Dealing with cravings”.

Next, the suggested labels for the fourth topic are "boost up spirit" and "self-empowerment". The discussion continued by looking at the similarities between these two labels. Through discussion, mental health professionals emphasized that there are many words related to self-empowerment in this topic group. In addition, they also expressed that AUD therapy encourages patients to come forward to admit past mistakes, take responsibility for change and believe in needing help from a more powerful external help. The results of the discussion found aspects of honesty, trust, surrender, soul-searching, integrity, acceptance, humility, willingness, forgiveness, retention, connection, and service. All mental health professionals reach a consensus to use "self-empowerment" as opposed to "boost up spirit" because it has a broader aspect than just boosting spirits.

All mental health professionals agree that the words (“regret”, “feel”, “bad”, “feel”, “worry”, and “think”) in the fifth topic are very coincidental with "dealing with lapses". During the analysis process, they connected their experiences of treating patients with the words in the list. Usually, the patients expressed their frustrations and started to regret drinking again, especially when they promised to change. Reference [61] also mentioned when patients notice that they still experience cravings, it can be worrisome. They believe they are doing it improperly and that they have disappointed their family and themselves. They are sometimes reluctant to even discuss ideas of using because they are so humiliated by the behavior. Therefore, it is not surprising that this topic is found in text messages for AUD therapy.

At the beginning of the discussion for the sixth topic, two mental health professionals (P1 and P2) each suggested "detoxification" and "keep sober". The followings are the explanations given by them.

P1: "*In my opinion, this is about how to maintain the changes that have been achieved. Even if the challenges are up and down, the patients can still stay with those change*s."

P2: "*The patient has stopped drinking but we still need to send text messages to the patient, aiming to maintain their achievement of days without alcohol...just like living a healthy life without alcohol.*"

After listening to each explanation given by mental health professionals, it can be understood that the topic is related to a healthy lifestyle without alcohol. Discussions continued to aim to develop the most appropriate label for the sixth topic. First, attitude retention is the most important content to convey. Second, detoxification occurs when the patient has stopped consuming alcohol, which is a state where there is no alcohol in the body. This has a similar meaning to "sober". Based on these, the meaning of the two terms is combined with the attitude of maintaining. Therefore, the term "maintaining sober state" was suggested, and it has gained consensus from all mental health professionals.

For the seventh topic, there are two suggested labels, namely "restructuring physical environment" and "relapse prevention". One of the mental health professionals stated that there are various therapy techniques in the prevention of relapse, including restructuring the environment. In this case, restructuring the physical environment is suggested by referring to words like "place" and "pub" in this topic group. However, the words in this topic group are not only focused on restructuring the physical environment, but rather they include a variety of relapse prevention therapy techniques. Other mental health professional thinks that there are many elements in relapse prevention, but it is mixed in terms of psychology and behavior. Examples of sentences that can be built for this topic are “avoid trouble places”, “always set a goal”, “be in control”, “keep positive”, or “stay away from pub”. As a result of the explanation given, a consensus was reached where all the experts agreed to use “relapse prevention” as a label for the seventh topic. The choice made is not just based on the words listed, but it reflects the fact that relapse prevention is why most people seek treatment [61].

Next, the eighth topic has words that clearly indicate that it is related to finance. Hence, this topic is labeled as “managing financial” and easily reaches the consensus of all mental health professionals. The ninth topic has words that clearly point to the effects of alcohol consumption on health. This makes it easier to name the topic as “consequences”. The content can emphasize what patients do or how patients feel as a result of their automatic thoughts [62]. In the discussion of the naming of the tenth topic, "drinking advice" was proposed by looking into all 20 words that were then considered usable in the construction of text messages. Other than that, "drinking limit measurement" was suggested for two reasons. First, the word "limit" can be for measurement or refer to drinking or drinking limit and measurement. Second, it cannot be denied that people with AUD cannot stop immediately; instead, they need advice from professionals in terms of consumption to reduce drinking [58]. The drinking limit is different for women and men [7]. Based on the justification given, the term “drinking limit”, which includes aspects of measurement, advice, and others that are related to the drinking limit, was agreed upon by all mental health professionals for the tenth topic.

In the next topic, the words (“urge”, “consider”, “interest”, “control”, “distract”, “fight”, “drive”, and “pass”) in this topic group are related to managing urges and distractions. Through interview analysis, it can be understood that mind diversion is a technique used in the field of psychology to encourage patients to think about other things when the urge to drink alcohol arises. A consensus was reached to use the term “dealing with urge”. The 12th topic was also easy to label as the wording was clearly directed towards planning before the patient went out for a drink, such as being prepared with taxi fare or having a friend drive him home. Therefore, the mental health professionals agreed to use the term "planning for safety" to label the topic. Then, discussing the 13th topic produced the terms “better life”, “healthy lifestyle”, and “lifestyle remedies”. After making connections with existing words such as “think”, “future”, “choice”, “life”, “clean”, “smart”, “sober”, “live”, “work”, “stay”, “charge”, “power”, “hope” and “sacrifice”, the mental health professionals reached a consensus to choose “lifestyle remedies” as the label for this topic.

For the last topic, two mental health professionals each suggested “careline support” and “support system”. The majority of mental health professionals agree that the support system is a more extensive term than careline support because it does not only refer to getting help through the online platform provided by mental health professional bodies, but support system also refers to strong social support a patient could get from friends and family. Despite the reciprocal nature of the relationship between social connectedness and mental health, social connection is crucial in fostering and maintaining mental health in the general population [63]. As a result of the discussion, a consensus was reached where all the mental health professionals agreed that “coping and support system” is a suitable label for the 14th topic.

From Table 2, it can be inferred that mental health professionals use text messaging to discuss a wide range of topics in AUD therapy, among which three topics are related to emotion treatment planning, while two topics on support and encouragement seem relevant to the AUD therapy context. Four topics, including “Dealing with cravings”, “Dealing with lapses”, “Relapse prevention” and “Dealing with struggle” are likely related to coping strategies, while two topics, “Managing financial” and “Drinking limits” could be regarded as topics derived from self-monitoring, because they are either fields affected by behavior change goal or self-action. Three topics are related to information on consequences, self-efficacy, and lifestyle remedies, respectively. From the results, it is interesting to know that mental health professionals encourage and motivate patients in terms of dealing with alcohol-related problems, sharing knowledge on consequences such as comparing the advantages and disadvantages, paying attention to emotion treatment planning on alcohol reduction, setting a goal, appointment, medication, and safety, as well as discuss the effect of maintaining sober state and lifestyle remedies together.

The qualitative analysis suggests that topic labeling depends on individual judgement and subject-matter expertise. One might have different knowledge or come from another school of thought; thus, they might not classify topics in the same way as the others do. Therefore, the involvement of mental health professionals in qualitative assessments through group discussion can improve topic labeling bias. However, for some real reasons, topic modeling has not been completely employed for document analysis and still requires human coding. First, the lack of information about word co-occurrences in short text data makes it difficult to identify document-topic distributions [23], [51], and [54]. Second, finding the meaning of words in short sentences might be challenging due to insufficient information. Third, the semantic connection and structure between two events are not entirely captured by the word co-occurrence [63].

In summary, topic modeling is helpful in determining topics and themes in text messages used for AUD therapy. The time and effort required to read through a large number of texts are significantly reduced when a topic modeling method is used. Additionally, the application of algorithms increases the consistency of topic prediction.

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# 5 Conclusion

Text messaging serves as a mental health mobile therapy for people around the world to reach professional help remotely. To the best of the authors’ knowledge, there is no similar research of topic modeling analysis conducted to explore the hidden topics inside text messages for AUD therapy. This paper has few contributions, firstly, it examines the potential of ten topic modeling methods in identifying topics in text messages sent by mental health professionals as AUD therapy. Secondly, the current study also contributes to the hidden content of text messages sent by a mental health professional in AUD therapy. The ten topic modeling methods used in this study demonstrate different capabilities in classification accuracy, clustering, and coherence. Although GSDMM and LDA performed well in coherence, this example of two-topic modeling did not perform well in accuracy and clustering. On the other hand, LFLDA, which topic modeling did not perform the best in coherence score, exhibits the best accuracy and clustering scores. Due to this, careful analysis and interpretation must be conducted. With the justifications discussed earlier, LFLDA with α = 0.05 and β = 0.01 is the most suitable method for identifying topics contained in text messages of AUD therapy used in this study. Other than that, 14 topics are found best to represent the 220 text messages in this study. With the application of LFLDA analysis on 220 text messages collected from previous literature on mobile therapy, a wide range of topics discussed in AUD text-based therapy is discovered. Concerning the AUD text-based therapy, theoretically, patients are taught how to deal with cravings, lapses and struggles, plan for alcohol reduction and safety, practice healthy lifestyle remedies, patients are given knowledge about financial management, and encouragement to maintain a sober state and develop a good support system. Based on the finding in this study, topic modeling is found feasible to identify latent topics in text messages used in AUD text-based therapy. Thus, topic modeling is practically useful as it can represent a form of a list which mental health professionals could refer to it when needed to choose suitable words in a selected topic. The findings also found that topic modeling is data dependent; hence, it relies on the practical requirements to conclude whether topic modeling is useful for finding hidden topics in documents. Nevertheless, results from the topic labeling indicate that the top 20 words produced by LFLDA are interpretable. It is known that employing more text message samples in topic modeling experiments will likely obtain more hidden topics. Moving forward, the application of more samples of text messages with the topic modeling method is needed for understanding the choice of words used in therapy and to capture more topics covered in AUD text-based therapy suitable to this targeted group of disorders. Additionally, researchers should undertake a preliminary study with several parameter settings to determine the best hyperparameter combinations for finding hidden topics before conducting an actual experiment with a larger sample dataset.

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