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Topic Modelling Analysis of Depression Therapy Text: A Preliminary Study

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ABSTRACT

The coronavirus disease 2019 (COVID-19) that has plagued the world since 2019 has initiated several issues and challenges in the mental health services field. World Health Organisation (WHO) recommended implementing remote mental health services such as telehealth to reach out to patients. One of telehealth services is text messaging therapy. Despite the challenges in treating depression via text messaging, the text messages for depression therapy that were built with different content renders this situation as a captivating subject for study. Nonetheless, the topics included in depression mobile therapy are scarce, particularly from the short text perspective. Fortunately, a machine learning technique known as topic modelling (TM) can be used to extracts topics from a set of documents without manually reading individual documents. It is very useful in searching for topics contained in short texts. This study aims to determine the topics in the text messages sent by mental health practitioners for depression therapy. In this study, three topic modelling techniques, i.e., Biterm Topic Model (BTM), Word Network Topic Model (WNTM), and Latent Feature Dirichlet Multinomial Mixture (LFDMM), were evaluated on 258 text messages of depression therapy. The performance of the TM techniques was evaluated using classification accuracy, clustering, and coherence scores. The findings indicate that the set of text messages comprises five topics. BTM performed better than the other techniques in classification accuracy and clustering in some cases based on the performance measures. Consequently, not much significant difference was found in the coherence score between the three topic modelling.

1. INTRODUCTION

The most common mental disorder is depression. Depression or major depressive disorder is a common but serious illness that usually affects mood and behaviour. Depression contributes to 4.3% of the global disease burden and is one of the most common causes of disability, predominantly among women (World Health Organization, 2021). Although this condition is serious, it can be treated. The development of tools and strategies involving digital technology and mobile self-care has the potential to be part of the support care

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system services. With the increase in mental health practitioners' awareness and initiative to reach patients remotely, several mental health mobile therapy tools were developed. Short Message Service (SMS), for example, has been widely used to support change in attitudes of individuals suffering from depression (Agyapong et al., 2021; Almeida et al., 2018; Shariful Islam et al., 2019). However, the study on the topics in the text messages meant to deliver depression therapy is scarce (Kerrigan et al., 2019).

Machine learning is a branch of computer science and artificial intelligent which focuses on the use of data and algorithm in predicting outcomes by first learning the way that things work. For example, neural language models and deep neural networks from machine learning was used to develop sarcasm identification framework on social media data (Onan & Tocoglu, 2021). Another work reported different types of deep neural network model provide promising results on text classification task involving sentiment analysis (Onan, 2022). In machine learning and natural language processing (NLP), topic modelling is a generative model that provides a probability framework for the frequency of occurrence of terms in documents from a corpus. Topic modelling is also guided only by the frequency of terms where word order information is not considered. This is also referred to as the word exchange assumption in a document, and this assumption leads to a bag-of-words model (Grün & Hornik, 2011).

Topic modelling methods can be in untrained or semi-trained forms, structured or unstructured data, and have the potential to be applied in various fields such as health, plantation, education, banking, social network opinion analysis, and data or transportation networks. It has been widely used to find latent abstract topics contained in a collection of texts such as documents, short texts, post text on Twitter or Facebook, and user comments on news pages, blogs, and emails (Albalawi et al., 2020). In contrast to traditional way of finding topics in documents, topic modeling is a useful method by means of utilizing software tools and algorithms to identify topics in a huge collection of documents effectively. This approach could enhance researchers' ability to interpret information meeting the needs of researcher in their applications.

2. TOPIC MODELLING

A topic modelling method known as Latent Dirichlet Allocation (LDA) and a package of topic models in R were used in the process of identifying themes related to self-injurious thoughts and behaviour (SITB) in a TeenHelp.org user discussion (Franz et al., 2019). Text related to depression posted on news articles before and after COVID-19 were discovered by Been and Byeon (2023) through their research using LDA. Meanwhile, LDA was used to analyse latent topics and the frequency of depression-related words extracted from post texts on Reddit sites (Tadesse et al., 2019). Due to sparsity problems in the short text, long text topic modelling such as LDA is less efficient in identifying latent topics (Yan et al., 2013). In the effort to overcome the sparsity problem, renewed LDA techniques have been developed by several researchers (Wu et al., 2020; Yan et al., 2013; Yang et al., 2020) to obtain more accurate topic modelling based on the characteristics of simple and short text messages. Each technique developed has different results on different text samples.

Self-aggregation-based topic model (SATM) was introduced in which short texts are aggregated for data sparsity (Quan et al., 2015). In particular, short texts are the results of randomly shredding lengthy documents produced by a common theme model. However, as the amount of data grows, the number of parameters also grows, increasing the computing cost and risk of overfitting. As a result, Pseudo-Document-Based Topic Modelling (PTM) based on pseudo-documents for short texts was introduced (Zuo et al., 2016). Similar to SATM, PTM automatically aggregates short texts, but it only allows each pseudo document to cover one topic, which cuts down on the processing time. To encourage semantically related terms under related topics, the Generalized Polya urn (GPU) expand the Dirichlet Multinominal Model (DMM) by leveraging word embeddings to produce more coherent and pertinent results (Li et al., 2016). Next, Generalized Polya urn Poisson-based Dirichlet Multinomial Mixture Model (GPUPDMM) was

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developed and was found to performs well but has a high time complexity due to the Gibbs sampling method used in the method (Tian & Fang, 2019).

A review on topic modelling had shown the advantages of utilizing these powerful tools in library management system including ontologies development, library services, scientometrics, management and organization of electronic resources (Lamba & Madhusudhan, 2022). Previous study conducted experiments on texts from six different sources using nine short text topic modelling techniques (Qiang et al., 2019). They discovered that each short text topic modelling produced different results for each dataset tested. According to Kinariwala and Deshmukh (2023) who conducted seven short text topic modelling experiments on Google News and Tweets, each performance of these techniques is dependent on the datasets. Through reading and to the best of the researcher's knowledge, the studies focusing on topic identification in depression therapy text messages using short text topic modelling methods are limited. Much short text topic modelling software can be used to identify topics in a document. However, the suitable topic modelling method for the depression therapy text message has not been determined. Thus, this study aims to determine the topics in the text messages sent by mental health practitioners for depression therapy and compare the performance of Biterm Topic Model (BTM), Word Network Topic Model (WNTM) and Latent Feature Dirichlet Multinomial Mixture (LFDMM) on depression text messages. BTM and WNTM are to be compared in this study due to their similarity of algorithms in applying global word co-occurrences based methods whereas LFDMM algorithm make use of pre-trained word vectors on large corpora which successfully surpasses the word sparseness in a short text. These characteristics of the three topic modelling algorithms are seen to meet the needs of this study which is to discover topics in short text.

2.1 Biterm Topic Model (BTM)

The key concept of BTM (Yan et al., 2013) is to learn topics contained in short texts based on the combination of two words in the whole corpus to solve the issue of sparseness in a single document. BTM assumes that the whole corpus is a mixture of topics, where the two words, known as the biterm, are independently generated from a specific topic. The BTM model topics use two words that co-occur together rather than a single word. The co-occurrence of two words can enhance the topic modelling than using only one word besides improving the topic learning. Moreover, BTM forms biterm from the whole corpus used together to learn topics rather than from a document. The approach helps to improve and uncover the latent topics by fully utilising the rich global word co-occurrence. The main advantage of BTM is that it uses the whole corpus as input, allowing the topic model to solve the issue of document shortness and better reveal the topic-word relations (Pietsch & Lessmann, 2018). The graphical model of BTM is shown in Fig. 1, and the generative process is described below (Yan et al., 2013).

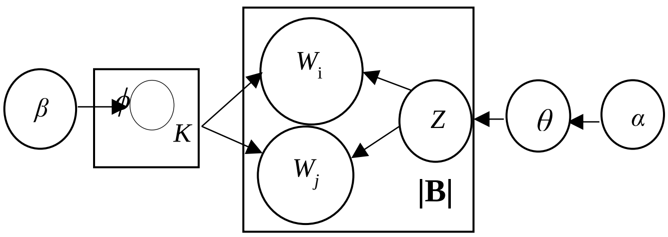

Fig. 1. Graphical model of BTM

For each topic z, draw a topic-specific word distribution $\phi_z \sim \mathrm{Dir}(\boldsymbol{\theta})$

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1. Draw a topic distribution $\boldsymbol{\theta} \sim \mathrm{Dir}(\boldsymbol{\alpha})$
2. For each biterm b in the biterm set B
   a) draw a topic assignment $z \sim \mathrm{Multi}(\boldsymbol{\theta})$
   b) draw two words: $w_i, w_j \sim \mathrm{Multi}(\phi_z)$

Different from BTM, WNTM models the distribution over topics for each word instead of learning topics for each document. The following explains WNTM generation process.

2.2 Word Network Topic Model (WNTM)

WNTM was introduced by Zuo et al. (2016) where the framework implements the same Gibbs sampling with LDA to reveal latent word groups in a word co-occurrence network. In the co-occurrence network, each word is known as a node. The connection between nodes is referred to as an edge. The connections between nodes indicate that these words have co-occurred at least once in the local context. In the original paper, a sliding window value of 10 is fixed to limit the size of the word network and to reserve only the local context for each word. The sliding window is used to scan words through the document; any two different words appearing in the same window would be treated as co-occurred. WNTM creates a new pseudo-document representing the word co-occurrence network to run the Gibbs sampling. A pseudo-document which contains all the words connected to it in the word network is created for every word. The difference between Gibbs sampling in LDA and WNTM is that in the former, LDA uses the original text document as an input, whereas WNTM uses the newly generated pseudo-document as input to topic modelling (Zuo et al., 2016). The graphical model of WNTM is shown in Fig. 2.

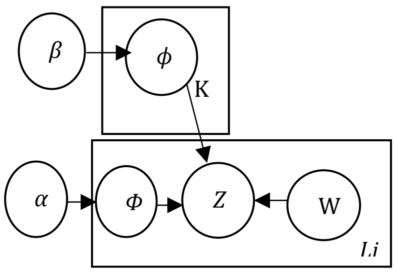

Fig. 2. Graphical model of WNTM

1. For each latent word group z, draw $\phi_z \sim \mathrm{Dir}(\beta)$, a multinomial distribution over words for z.
2. Draw a latent word group distribution for the adjacent word-list Li of the word w_i, $\Phi_i \sim \mathrm{Dir}(\alpha)$.
3. For each word $w_j \in L_i$:
   a) select a latent word group $z_j \sim \Phi_i$
   b) select the adjacent word $w_j \sim \phi z_j$

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In summary, BTM and WNTM learn the latent topics from the global word co-occurrences obtained from the documents, relying on the idea of the closer the two words, the more relevance the they are. Next, the following explains LFDMM generation process.

2.3 Latent Feature Dirichlet Multinomial Mixture (LFDMM)

LFDMM combines the latent feature and Dirichlet Multinomial Mixture (DMM) models. This model assumes that there is only one topic in each document. In LFDMM, pre-trained word vectors trained on large corpora were used to incorporate information from large datasets. Therefore, LFDMM surpasses the word sparseness in a short text. Generally, LFDMM has the structure of the original Dirichlet multinomial topic models, with additional two matrices, where τ_t is the latent feature vector associated with the topic (t) and ω_w is the latent feature vector associated with the word (w). To generate a document in a document using LFDMM, a distribution over the topic is sampled for the document collection. Next, LFDMM draws a topic indicator for the whole document. A binary indicator variable is sampled from a Bernoulli distribution, Ber(λ), for each word in the document, which will be used to determine either the Dirichlet multinomial or latent feature component to generate the word. Lastly, the selected component will generate the word from the same topic. The hyper-parameter, λ, is the probability of a word being generated by the latent feature model. The graphical model of LFDMM is shown in Fig. 3 and generative process of LFDMM is as follows (Nguyen et al., 2015).

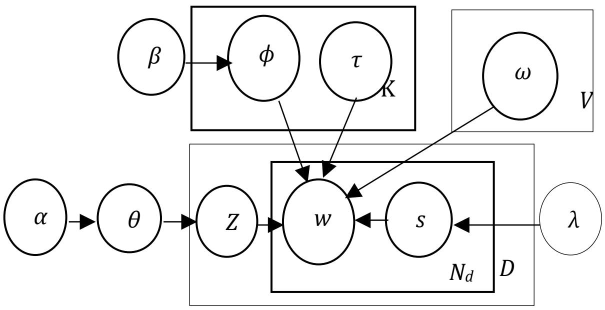

Fig. 3. Graphical model of LFDMM

1. Topic document distributions is drawn, $\theta \sim Dir(\alpha)$
2. Topic word distribution is drawn, $\phi_z \sim Dir(\beta)$
3. Topic indicator is drawn for the entire document d, $z_d \sim Cat(\theta)$
4. A binary indicator is sampled from a Bernoulli distribution, $s_{di} \sim Ber(\lambda)$
5. Word generated, $w_{di} \sim (1 - s_{di})Cat(\phi_{zd}) + s_{di}\, CatE(\tau_{zd}\, \omega^T)$

3. METHODOLOGY

This study was conducted in Intelligent Data Analytics lab at Institute of Visual Informatics, Universiti Kebangsaan Malaysia, from October 2023 to November 2023. Several experiments were conducted on the sample of text messages used in depression therapy. These were done to examine the best performing topic models for the type of text message samples in this study. The experiments were conducted on a Windows

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10 Pro with Intel(R) Core(TM) i5-6200U CPU and 8GB RAM. The data source and pre-processing tasks are presented in the following section. Fig. 4 below shows the flow of research methodology of this study.

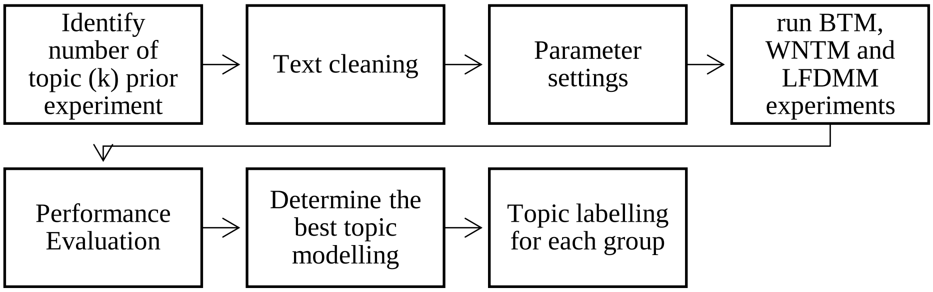

Fig. 4. Research flow of analysis on depression text therapy using topic modelling

3.1 Data Set

This study focuses on text messages used by professionals in treating depression, where the treatment targets different types of primary and secondary outcomes. The dataset was developed by collecting text messages for depression therapy from previous studies. The text messages were collected from published studies between 2009 and 2020 (Aguilera et al., 2017; Agyapong et al., 2018; Almeida et al., 2018; Anstiss & Davies, 2015; Barrera et al., 2020; Hartnett et al., 2017; Kraft et al., 2017; Ranney et al., 2017; Shariful Islam et al., 2019). Text messages can be found either in the main content section of the article or the appendix section. Consequently, 258 text messages made up the dataset for this preliminary study. The number of topics (value of K) needs to be determined before the text messages can be used as the dataset in the experiment. One way is using the manual topic distribution through a qualitative approach. In this process, each text message content was analysed by an expert in mental health counselling. The interpretation of the text messages depends on the expert's judgement and knowledge in the mental health therapy context, psychology theories and practices. Each of the text messages were assigned to at least one label. Meanwhile, some text messages have more than one label and share the same label with other text messages (Fig. 5). This leads to the nine labels assigned to the text messages dataset, as shown in Fig. 6. Table 1 provides a short description of each label. Some pre-processing steps are performed, including eliminating stop words, removing numbers, converting all text to lowercase, and lemmatisation. The statistics of the dataset include 2656 words, 377 unique words, maximum length of a sentence is 14 words, 9.14 words per sentence on average, 1438 letters and 51.36 letters per sentence.

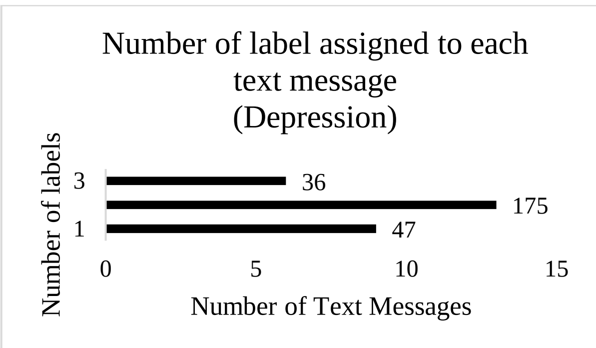

Fig. 5. Number of labels assigned to each text message

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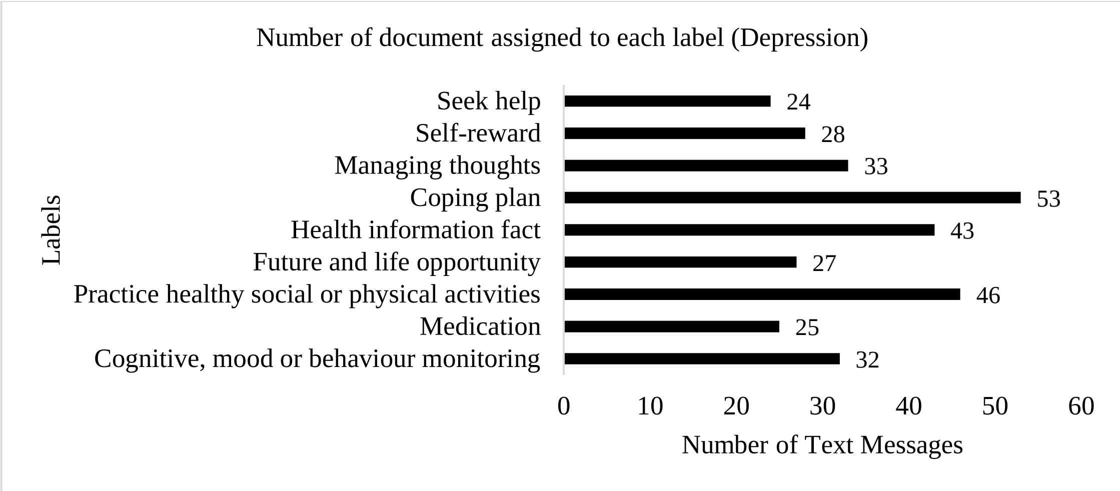

Fig. 6. Number of text messages assigned to each label

Table 1. Short description for each label

Label	Short description
Cognitive, mood or behaviour monitoring	Monitoring on thinking pattern, current mood or behaviour
Medication	Anything related to medication such as adherence, appointment, reminder or side effect
Practice healthy social or physical activities	Content talks about activities that help
Future and life opportunity	Pay attention to things that can change for a better future by taking opportunities. Forget about yesterday and the past.
Health information fact	Fact about depression, health, treatments, symptoms, drinking habit etc.
Coping plan	Method to control or change mood and behaviour
Managing thoughts	Method to shift negative thinking to a positive one
Self-reward	Appreciate self-effort and hard work by using any form reward
Seek Help	Provide help care contact or encourage patient to ask for support from family/friends/professionals.

3.2 Parameter Settings

This study applied the open-source Short Text Topic Modelling (STTM) with a JAVA-based library (Qiang et al., 2019). The software contains all three short text topic modelling techniques: BTM, WNTM, and LFDMM. For the hyperparameter settings, two studies used smaller α values ($\alpha = 0.05$) within the LDA experiments (Cheng et al., 2014; Schneider & Vlachos, 2018). In contrast, other study used $\alpha = 0.1$(Wang et al., 2016). BTM also worked well when $\alpha = 50/K$ (Cheng et al., 2014; Qiang et al., 2019). Moreover, the smaller value of $\beta = 0.01$ was also used in some studies (Cheng et al., 2014; Nguyen et al., 2015; Qiang et

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al., 2019; Wang et al., 2016; Yan et al., 2013) when applied to the short text. Based on these values, the smaller value of hyperparameter settings is assumed to be suitable for short texts. The small value of α indicates that short text documents contain less topic, while the smaller β value is associated with topic word-sparseness (Pietsch & Lessmann, 2018). The same hyperparameter settings were used to compare the three models in this experiment, with $\alpha = 0.05$ and $\beta = 0.01$. For BTM, each document is treated as one window. For WNTM, the window size is set to 10 words. BTM, WNTM and LFDMM run for 2000 iterations, which is generally sufficient for convergence. LFDMM iteration baseline model was run 1500 times and use the sample produced by the baseline model to initialize the LFDMM with further 500 iterations (Nguyen et al., 2015). For LFDMM, λ is set to 0.6, which has shown in the past study that after combines data from bigger external corpus with corpus-specific topic-word multinomials, better word-topic distributions were produced in this way (Nguyen et al., 2015). In addition, LFDMM techniques are based on the concept of word embedding. In this experiment, "glove.6B.300d.txt" pre-trained word embeddings were used. Subsequently, each model was run with 6 different number of topics (K), from 5 to 20, with a step size of 3. The range for K was selected based on the number of labels assigned by an expert from the previous stage. The minimum value of K is very close to nine, i.e., the original number of the labels. On the contrary, the maximum limit value of the topic for this experiment is 20, considering the significant differences observed between the considerable K values and the ability of the researcher to assess the topic manually. The step size of three was chosen because each document has at least one label and three labels at the most. This procedure is also used by Pietsch and Lessmann (Pietsch & Lessmann, 2018).

3.3 Performance Evaluation

According to Asmussen and Moller (2019) the outcome produced by the model can be used to assign labels to the topic group. Likewise, other studies also implemented text processing algorithms to measure classification accuracy, prediction score, coherence, and clustering (Howes et al., 2013; Nguyen et al., 2015; Pietsch & Lessmann, 2018; Qiang et al., 2019). In this study, both quantitative and qualitative perspectives are used. From the qualitative perspective, a manual analysis of the words extracted from the experiment for each topic was done to interpret their meaning and assign a topic label. The output of the models is the list of the most probable words in a topic. The top 20 most probable words in each topic group are presented to a group of 6 experts for interpretation and labelling. These experts have at least five years' experience in depression counselling. They were invited through email, and a consent form was filled out as an agreement to partake in the manual analysis. Next, an online meeting was conducted with the experts to analyse the top 20 words in each topic and discuss the suitable topic to be assigned to each topic group. The discussion lasted for two hours.

The topical document evaluations were conducted using document classification accuracy, clustering, and coherence for the quantitative measurement, as included in the STTM package (Qiang et al., 2019). Classification accuracy is used to measure document-topic distribution. Ideally, each document (text message in this study) is assigned to a topic with the highest probability using the document-topic distribution $p(z \mid d)$. The text classification accuracy is used to evaluate the performance of BTM, LFDMM, and WNTM. In the STTM package, the default setting of the linear kernel Support Vector Machine (SVM) classifier in LIBLINEAR (https://liblinear.bwaldvogel.de/) was used. Fivefold cross-validation was performed on the dataset to measure its classification accuracy. A higher accuracy indicates that the model could better discriminate the learned topic. It also means that the learned topics are more related to the real dataset topics. Clustering is another important evaluation that directly measures the effectiveness of a topic model without the influence of external methods (Yan et al., 2013). In document clustering, each topic is treated as a cluster. After the topic probability calculation was performed, each document (d) was assigned to the topic (z) with the highest probability $p(z \mid d)$. The two most common clustering metrics, Purity and Normalised Mutual Information (NMI), are used in this study for clustering evaluation. The good clustering value is close to 1, while bad clustering is close to 0. Next, coherence evaluation is conducted to measure

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the quality of topic-word distribution. A coherence score is based on the concept that words belonging to the same topic will co-occur in a document. It is noteworthy that the coherence score is only reliable for measuring frequently found words in a document. This is because the less frequent word is unreliable in calculating the topic-word distribution (Yan et al., 2013). In this experiment, one Wikipedia meta-document was used to compute the score of topic coherence. Point-wise Mutual Information (PMI) of each word pair was calculated using a 10-word size sliding window and considering the word co-occurrence from the entire dataset of Wikipedia articles.

4. RESULT

Six different topics were run using hyperparameter combinations of $\alpha = 0.05$ and $\beta = 0.01$ for each topic modelling. Each model was run 20 times, and the mean performance of classification, clustering, and topic coherence was reported.

4.1 Classification Accuracy

The classification accuracy of text messages for depression therapy using three topic modelling is shown in Table 2. LFDMM exhibits a higher accuracy score than the WNTM method. However, BTM outperforms the other two methods except with LFDMM when K = 5. Overall, the results show that the biterm word co-occurrence performs better than the word embedding and co-occurrence network method for the depression domain dataset. Although BTM and WNTM are word co-occurrence methods, the better performance of BTM could be due to the use of the whole corpus as an input, while WNTM generates document-topic distribution learned from pseudo-document. This is in line with other findings stating that BTM achieved better classification accuracy than WNTM (Qiang et al., 2019; Schneider & Vlachos, 2018). Thus, this shows that generating a new pseudo-document based on the word context does not necessarily mean it is sufficient to overcome the tendency of the topic inference under data sparseness (Schneider & Vlachos, 2018). In contrast, other studies report that WNTM performed better than BTM in classification accuracy (Pietsch & Lessmann, 2018; Yi et al., 2020). It indicates that the performance of topic modelling is dataset-dependent. Overall, BTM and LFDMM show an upward trend as the value of K increases, whereas WNTM shows an unstable up and down trend across the K values. It signifies that WNTM is less reliable in making document-topic distribution for depression datasets than the other two methods. Notably, the classification accuracy scores for both BTM and LFDMM decrease when K = 11 despite the comparatively small differences.

Table 2. Mean classification accuracy of three topic modelling with alpha = 0.05, beta = 0.01 and different values of K

Number of topics (K)	BTM	WNTM	LFDMM
5	10.71429	7.678575	13.21429
8	18.39285	6.964289	13.75000
11	18.03571	9.821428	13.57143
14	19.28571	8.035713	14.28571
17	21.42857	9.285723	18.21429
20	20.71427	8.214291	17.32143

4.2 Clustering

Short text clustering is one of the most important aspects of short text topic modelling as it helps find targeted patterns from the dataset. The result of the clustering evaluation is reported in Table 3. The data report the average purity and NMI scores of each modelling on depression datasets. Purity and NMI scores range from 0 to 1, and the closer the value to 1.0, the better its clustering performance (Nguyen et al., 2015).

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The highest score of purity and NMI of each modelling comprising different K values are highlighted in bold. Overall, all models produced upward trends with an increasing number of topics. Although BTM achieves the highest accuracy score in most K values, its purity and NMI scores are the lowest among all methods. It signifies that BTM is the worst in labelling sample text messages into their cluster compared to the golden label among all methods. The differences in purity and NMI scores among the methods are comparatively small. Although WNTM performs best on clustering evaluation, it performs the worst in classification accuracy evaluation.

Table 3. Mean clustering score of three model with alpha = 0.05, beta = 0.01 and different values of K.

Number of topics (K)	BTM		WNTM		LFDMM	
	Purity	***NMI***	***Purity***	***NMI***	***Purity***	***NMI***
5	0.4142	0.4163	0.3928	0.4147	0.3839	0.4224
8	0.4803	0.5208	0.4678	0.5016	0.4482	0.4988
11	0.5410	0.5716	0.5410	0.5710	0.5375	0.5541
14	0.6250	0.6206	0.6375	0.6335	0.5964	0.5891
17	0.6946	0.6574	0.7428	0.6875	0.6857	0.6404
20	**0.7464**	**0.6788**	**0.7946**	**0.6977**	**0.7678**	**0.6812**

4.3 Topic Coherence

Topic coherence evaluates the quality of topic-word association by measuring how well the word is assigned to a topic (Nguyen et al., 2015; Qiang et al., 2019). Based on Table 4, it can be observed that WNTM and LFDMM show higher coherence scores than BTM in most K values. However, the performance is inconsistent, where the scores increase when K = 17 and decrease again when K = 20. Overall, the three methods produce downward trends with an increasing number of topics. This could be assumed that not many good topics can be produced when K increases as the sample data used were all short text messages consisting of limited words. Another reason is that the increase in K will only lead to a meaningless topic and less coherence. Therefore, K = 5 will be considered the best number of topics for sample data on depression in this study.

Table 4. Mean coherence score of three models with alpha = 0.05, beta = 0.01 and different values of K.

Number of topics (K)	BTM	WNTM	LFDMM
5	0.592458	0.596730	0.600214
8	0.588065	0.593505	0.598672
11	0.587301	0.590957	0.580718
14	0.583307	0.582768	0.579854
17	0.577075	0.695082	0. 598182
20	0.571340	0.569066	0. 594948

A notable huge distance between BTM classification accuracy scores and the other two methods indicates that BTM is a suitable option for topic modelling for the depression dataset in this study. An acceptable clustering score and a consistent performance in coherence evaluation indicate that BTM is a promising topic modelling method for the depression dataset of this study. The coherence evaluation also shows decreasing scores for all methods with an increasing number of topics. It can be said that there is still one good topic found in those methods regardless of the number of topics. On the contrary, the decrease

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of coherence scores for all methods when K >= 8 signifies that the higher the number of topics, the poorer the topic-word distribution. Besides, the value of K = 5 is also significant to be considered the most suitable number of topics because it is close to the original label, which is nine.

4.4 Efficiency

This section compares the efficiency of the three methods on depression text messages. Table 5 reports the mean initiation time and per iteration time in milliseconds for each method. From the results, BTM performs the best. As expected, LFDMM performs the slowest because it needs more time to optimise topic vectors and runs more iterations than the other two methods. WNTM is slower than BTM possibly due to the time needed to find word co-occurrence and the process of creating pseudo-document. According to Qiang et al. (2019) the word embedding method (LFDMM) has the slowest initiation time due to computational steps for the similarity between words. Therefore, it is not surprising that LFDMM performs the slowest in this study.

Table 5. Topics in text messages for depression therapy produced by BTM.

Topic Model	Initiation Time (millisecond)	Per Iteration Time (millisecond)
BTM	7.0	0.144
WNTM	62.0	0.355
LFDMM	156.0	35.988

4.5 Topic Labelling – Qualitative

This section reports the interpretability of the topics using a qualitative approach. A group of six experts from the depression counselling domain was involved. As discussed in the previous section, the topic modelling method used for topic interpretation is BTM with the K value of 5. In contrast to WNTM and LFDMM, BTM showed better performance in classification accuracy scores, an acceptable clustering score and a consistent performance in coherence evaluation. These indicate that BTM is able to unleash meaningful topic in depression therapy dataset. In topic labelling process, the experts were given a list of five topics, where each topic has the top 20-word order by word probability. The first word has the highest probability, and the last word has the lowest probability of being generated by the topic. Table 6 presents the model's five topics, including the top 20 words. Some words appear in every topic (as underlined), but only a few words are unique to one topic, such as "work," "far," and "reward" for Topic 1. The interpretation and topic labelling were conducted in a 2-hour online meeting, where all six experts discussed and shared their opinions on the words listed for each topic. The experts interpreted the topics by analysing the top 20 words. During the discussion, the experts identified common words from the list they had always used during depression text-based therapy. The experts also related coherent words to the psychotherapy element they have been practising. Two to three labels were suggested during the discussion, with the most relevant words related to it listed together to get a clearer justification. Some of the words could not fit into any topic label suggested by the experts. Thus, those words are considered less coherent to the topic. The experts then discuss each suggested label and share their opinions before selecting the most suitable label.

Table 6 shows the five topics with their labelling. For example, topic 1 is about Life Style Remedies with words such as "do," "friends," "work," "far," "fun," "reward," "coffee," "activity," "movie," "day," "place," and "call."

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Table 6. Topics in text messages for depression therapy produced by BTM.

Topic	Topic Labeling	Top 20 words
1	Life Style Remedies	do friends work far reward hard bad think plan something remember fun get coffee activity go movie day place call
2	Close Monitoring	do today think tomorrow feel stress present change take opportunity determine rise up advantage mood something scale sad angry piss
3	Cure, Recovery and Treatment	activity mood think improve positive today low feel attention impact note refer hit point try thing good negative thought value
4	Treatment Adherence	first take medication feel go day help thought stress side effects stick initial discomfort last few plan little future sometimes
5	Support and Motivation	lie success today stumble block become step stone better life adversity opportunity discourage problem turn behind before tiny matter compare

5. DISCUSSION

This paper aimed to identify the content of text messages sent by a mental health professional as depression therapy. Previous studies have focused on lifestyle and remedies in depression therapy, such as nutrition and physical activity in depression therapy interventions (Looijmans et al., 2017; Navarro et al., 2020; Young et al., 2022). A longitudinal study (Velten et al., 2018) has proven that irregular social rhythms, smoking, and a vegetarian diet contributes to mental health problem among German and Chinese students. Thus, text message therapy focusing on lifestyle seems necessary and relevant to improving mental health.

The Close Monitoring topic covers the text content that requires patients to rate their current feeling and mood based on a certain scale. Some text messages sent to patients also encourage patients to text back about their thoughts and activity (Aguilera et al., 2017; Ranney et al., 2017). Moreover, text messages are useful in self-monitoring depressive symptoms (Keding et al., 2015). Based on Table 6, all words listed are considered representable of Topic 2. Next, the experts in this study agreed that the words listed are all meaningful and related to Cure, Recovery, and Treatment, as shown in Topic 3. The experts also mentioned using those words in the depression therapy sessions.

Some text messages in this study were constructed in the context of treatment adherence. For example, some text messages encourage patients to continue with clinic appointments, taking medicine, treatment follow-up, and consultation with professionals (Aguilera et al., 2017; Almeida et al., 2018; Välimäki et al., 2017). Text messages that embed supportive and motivational senses help manage follow-up care and medical appointments (Agyapong et al., 2016). Supportive and motivational text messages also leave positive sentiment in patients, motivating them to persevere with the treatment, grab any opportunity, be open to taking part in new activities, and promote positive thinking.

Overall, the experts in depression counselling domain found that the top 20 words produced by topic modelling are interpretable into topics. The qualitative evaluation implies that topic labelling can vary depending on human judgement and knowledge in the area. One expert might not have the same idea of topic labelling as the others. Furthermore, the involvement of experts in qualitative evaluations through group discussion can reduce human biases in topic labelling. Nonetheless, topic modelling has not been used entirely for document analysis and still requires human coding for some factual reasons. First, the data sparseness under the context of short text data is a challenge in finding document-topic distributions caused by limited word co-occurrence information (Shi et al., 2019; Yang et al., 2020; Yi et al., 2020). Second, limited information in the context makes it difficult to find the meaning of ambiguous words in the short texts. Third, the word co-occurrence does not fully capture the semantic relationship and structure between words (Yi et al., 2020). This also contributes to difficulty in identifying the hidden meaning of a sentence.

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Nevertheless, topic modelling is useful in identifying topics in depression therapy text messages. Most importantly, using a topic modelling algorithm reduces the time and effort of going through a large number of documents (Asmussen & Moller, 2019). Besides, the use of algorithms provides more consistency in predicting topics. Human coders such as the experts in this study tend to suggest different topics based on their background, knowledge and experiences, which is inconsistent among the experts.

6. CONCLUSION

This paper investigates the potential of three topic modelling methods to identify topics in text messages sent by mental health professionals as depression therapy. Based on this study, topic modelling is feasible in identifying hidden topics in depression therapy text messages. Although the three topic modelling methods used in this study have different capabilities in classification, clustering, and coherency, with BTM exhibiting the best accuracy score, WNTM performs better in clustering, while WNTM and LFDMM showed a higher score in coherence than BTM, the differences are comparatively small. Due to this, careful analysis and interpretation must be conducted. With the justifications discussed earlier, BTM is the most suitable method for identifying topics for the dataset of this study. It depends on the practical requirement to say whether topic modelling is appropriate to discover topics in documents. The qualitative approach used in this study shows that the top 20 words listed by BTM are interpretable. From the experiment, five topics are found to represent the 258 text messages in this study. It is assumed that the number of topics discovered by topic modelling can be more when using more text message samples in an experiment. Based on this valuable finding, it is noteworthy that a preliminary study needs to be conducted with different parameter settings for the researcher to decide the parameter combinations with the most efficient in making topic modelling before an actual experiment is carried out with a bigger sample dataset.

This study came with some limitations, firstly, the study focused on English short text messages which may not be able to generalized to other cultural context. Secondly, this study experimented on depression therapy settings, which may limit the generalizability of the findings to types of mental health problems. Future study should consider use bigger dataset, different languages, other mental health problem and mixture of parameter settings to provide more wide-ranging insights of topic modelling application in finding mental health therapy topics.

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8. CONFLICT OF INTEREST STATEMENT

The authors have no competing interests to declare.

9. AUTHORS' CONTRIBUTIONS

Teh Faradilla Abdul Rahman: Conceptualization; Data curation; Formal analysis; Writing - original draft; Investigation; Methodology; Project administration; Validation; Visualization; Resources; Software; **Raudzatul Fathiyah Mohd Said**: Formal analysis; Writing - original draft; Investigation; **Alya Geogiana Buja**: Conceptualization; Writing - original draft; Investigation; AL: Writing - original draft; Visualization; **Norshita Mat Nayan**: Supervision; Project administration; Resources; Writing - review & editing

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