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When Machine Meets Mind: A Two-staged Literature Review on AI Applications in Mental Health

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ABSTRACT

Mental health problems have brought a serious impact on people's quality of life and health. With the development of technology, the emerging technologies such as artificial intelligence (AI) (combined with Big Data) has the potential to become new means of intervening in mental illness. This study analyzes the abstracts of the relevant literature involving the applications of AI in the field of mental health through dynamic topic modelling. Nine main research topics are extracted and analyzed. Then we identify current research hotspots and possible future directions by analyzing the evolutionary trends of these topics over time. In the future, the representative literature will be searched and reviewed based on the extracted topics to comprehensively and deeply explore the applications status and potential of these technologies in the field of mental health.

Keywords: Mental health, DTM, artificial intelligence, evolutionary trends.

INTRODUCTION

Mental health issues are always a serious problem to the society and it gains increasing attention globally in recent years. Traditional mental health services are facing challenges such as unequal distribution of resources and limited accessibility of services (Saxena et al., 2007), although they have brought substantial benefits. With the advent of the digital age, artificial intelligence technology offers a complementary solution to the traditional mental health services. In addition to expanding the access to more people, it also improves the accuracy of predicting mental health problems and the efficiency of personalized treatment plans by analyzing large amounts of medical data (Johnson et al., 2021). While research on AI in mental health is increasing, there are still some issues that need to be tackled with, such as ethics and privacy (Graham et al., 2019) and the necessity to keep increasing the accessibility (Chen et al., 2019), etc.

There has been a considerable accumulation of research on the use of AI in mental health, as indicated by the significant rise in the total number and citations of literature on AI for the treatment of a particular mental illness (Tran et al., 2019). There are some literature review studies to address the issues of AI applications in mental health (e.g., D'Alfonso, 2020; Graham et al., 2019). These studies rely on manual literature retrieval and content summary, which are time-consuming. The views are also subject to a certain degree of subjective influence. Therefore, there is lack of research using AI techniques to explore the application of AI in mental health, which allows us to objectively understand the state of the research in this field to date and identify new trends for the emerging research (Bai et al., 2021). The purpose of this study is to fill in these research gaps by exploring in depth the research topics of AI in mental health and their evolutionary trends over time based on a two-staged literature review. The first stage, which is our current research, uses the dynamic topic modeling (DTM) to streamline the selected literature abstracts. The second stage, i.e., the follow-up study, will retrieve representative literature based on the topics generated in the first stage. By analyzing the literature over the years, we can track the pulse of development of these topics over time and identify some research gaps.

The purpose of this study is to (1) reveal the major topics of AI research in the field of mental health, and (2) analyze the evolutionary trends of these topics over time. Through this study, we expect to provide researchers and practitioners in the field of mental health with a macroscopic perspective that will help them to understand current research hotspots and future directions.

RELEVANT STUDIES

Literature Review on AI in Mental Health

In the traditional systematical literature review on the application of AI, the authors manually screen and retrieve some literature, and then manually summarize and analyze the topics related to the research status and future development direction. The methodology employed in the previous works remains predominantly traditional. These processes include (under different literature databases): keyword search (single or multiple), manual screening, reading and evaluation, organization and summary (e.g., Ray et al., 2022; Zhou et al., 2022), which are primarily relying on manual approaches that may be time-consuming and labor-intensive. The fast-developing AI technique (DTM) can be used for the literature selection and literature review.

The previous review articles often have specific research focuses, such as the effectiveness and potential of artificial intelligence in predicting and classifying mental health disorders (e.g., Chung & Teo, 2022; Graham & Depp, 2019; Verma et al., 2024). There are only a few review articles that focus on multi-aspects. For example, D'Alfonso (2020) review the literature with different topics, such as 1) human perception or digital phenotypes, 2) natural language processing of clinical text, social media content analysis and 3) chatbot technology. In addition, all of these studies are conducted in with a static method. Using dynamic topic modeling, this study aims to review the research literature on AI applications in mental health, including the above review articles, in a more comprehensive and dynamic way.

Dynamic Topic Modeling

Topic modeling is a text mining technique that aims to find hidden topics from a given collection of text and assign topics to each document. It has been applied to extract topics and hotspots in various fields since it was proposed. The most commonly used is LDA. DTM is a topic model for exploring topic changes over time based on a Bayesian statistical framework that introduces a time dimension based on LDA (Blei & Lafferty, 2006). It can obtain the topic distribution of each document, with each topic (consisting of multiple topic words) changing over time to better model the development and evolution of topics over time series (Pavithra & Savitha, 2024). At the same time, it reduces human bias, subjectivity and error.

RESEARCH METHODOLOGY

In order to depict the key issues on AI (combined with big data) applications in mental health and the trend of research hotspots over time, we used DTM model to summarize the topics of the obtained abstracts. Then we used heat map to show the trend of the hotness of their topics over time. The complete process of topic modeling using DTM is shown in Figure 1.

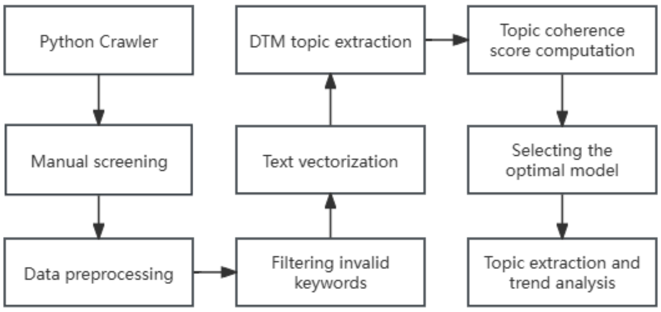

Figure 1: The overall research process

Data Collection

Considering professionalism, resource richness and network, this study used China National Knowledge Infrastructure (CNKI) as the data source. Python web crawler technology was used to retrieve English literature abstracts in the fields of psychology and psychiatry from CNKI database between 2003 and 2023. The search terms "artificial intelligence" and "big data" were used to search the literature. Due to the problems of literature classification, anti-crawling mechanism, and partial literature abstract display on CNKI, there are few relevant articles we could crawl to, and the number of articles retrieved every year is between 0 and 49. We did a simple manual screening of the collected data such as language screening (English required), content screening (to determine if it really belongs to the category of AI applications in mental health). Finally, 390 abstracts of literature in the AI category were identified.

Data Preprocessing

Basic Processing

First, we used the python regular expressions to remove the non-text content, including special symbols and some numbers. The second step was synonymous substitution, including the conversion of uppercase to lowercase letters and the replacement of full names with acronyms. And third, we performed the operations of word segmentation, removing stopwords and lemmatization. These works remove redundant information and avoid the performance degradation of the model caused by the introduction of invalid information.

Invalid Topic Words Screening

Low-frequency words and high-frequency nonsense words can greatly reduce the efficiency of modeling and the interpretability of results. According to our observation, high-frequency meaningless words in topic modeling results can make the final generated topics contain almost all of these words, which is not helpful and even disruptive. Term Frequency and Inverse Document Frequency (TF-IDF) is a technique commonly used for term weighting (Kadhim, 2019). The TF stands for Term Document Frequency, i.e., how often a word appears in a document. As shown in formula (1), where t is a specific word and d is a document, it is calculated by the frequency (n) of a word t in a document d divided by the total number (N) of words in the document d. IDF denotes Inverse Document Frequency, i.e., a measure of the importance of a word in all documents. As shown in formula (2), where D represents the total number of documents and df(t) represents the number of documents containing a specific word t. Logarithm can avoid the problem of too large value and ensure the monotonically decreasing characteristic of IDF. The higher the TF value, the more important the word t is in the document d. However, a higher IDF indicates that the term is more unique and valuable for distinguishing documents. We multiplied them to get the TF-IDF value for each word in a document. As shown in equation (3), it represents the importance of this word in all documents. Words with too low TF-IDF values contribute little to the document, and words with too high values cannot distinguish the document topics. Therefore, TF-IDF has been used as a word filtering tool for topic modeling in some studies (Chen et al., 2017).

$$\mathrm{TF}(\mathrm{t},\mathrm{d}) = \frac{\mathrm{n}}{\mathrm{N}} \tag{1}$$

$$\mathrm{IDF}(\mathrm{t}) = \log_{\mathrm{e}}\frac{\mathrm{D}}{\mathrm{df}(\mathrm{t})} \tag{2}$$

$$\mathrm{TF}-\mathrm{IDF}(\mathrm{t}) = \mathrm{TF}(\mathrm{t}) * \mathrm{IDF}(\mathrm{t}) \tag{3}$$

The average TF-IDF of each term in each document is taken as the TF-IDF value of the term. The distribution of our vocabulary TF-IDF values is close to continuous. Therefore, we first looked at the graph of Cumulative Distribution Function (CDF) distributions of the TF-IDF values of the documents, as shown in Figure 2. CDF is one of the commonly used concepts in probability theory and statistics, where it gives the probability of being less than or equal to a particular value taken. As shown in Figure 2, there are no obvious low-frequency words in the documents. And the CDF curves of the words almost always enter a flat state after steadily increasing to a certain level. Eventually we chose 0.005 as the TF-IDF thresholds for the word lists of articles. The partial words larger than this threshold in the word lists of articles are shown in Table 1.

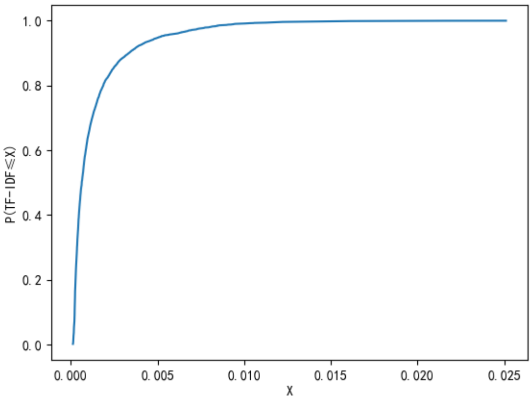

Figure 2: CDF distribution of TF-IDF for AI related articles

Table 1: Part of the words in the AI document greater than 0.005

Words	TF-IDF
ai	0.025108
predict	0.021670
model	0.019627
...	...
benefit	0.005017

We observed that although some words have high frequency in the TF-IDF dimension, they are not meaningless for topic extraction and we cannot removed all words larger than a threshold. Therefore, we artificially filtered out some meaningless words such as “however”, “ai”, etc. They often fail to account for thematic differences.

Text Vectorization

In order to facilitate the calculation and analysis, the experiment used the corpora module of the genism library to build the dictionary and bag-of-words model for the word list after word segmentation in the text. Then the word frequency vector was used to represent the segmented text.

Topic Extraction

Optimal Number of Topics

Determination of the number of topics is crucial for literature topic extraction. A commonly used method to determine the number of topics is based on the topic coherence scores. In this study, we created DTM models with topic numbers ranging from 2 to 20 for AI literature abstract texts. For the DTM model with the number of topics k, the average topic coherence score in n time slices was calculated as its topic coherence score. Figure 3 show the variation of topic coherence scores with the number of topics for the DTM models. It can be seen from the figure, when the number of topics is 9, the topic coherence score of model arrives the highest.

Topic Extraction

The genism library was used in the study to build the DTM model. Genism provides two ways to create a DTM model. By comparison, the approach using the native dtm-win64.exe model not only has a relatively high topic coherence score, but also runs faster.

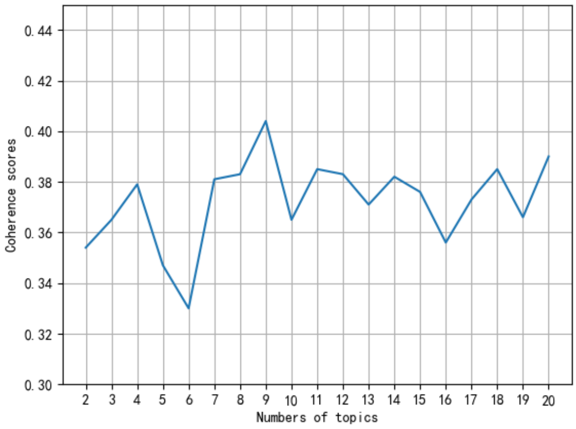

Figure 3: Situation of topic consistency score of AI articles

RESULTS

Topics Extracted

Finally, nine topics were extracted by the DTM and named by the authors based on the corresponding key topic words. Topic consistency is our main consideration. When determining the number of topics, we used word co-occurrence frequency and similarity to measure the internal consistency of topics. We also paid more attention to its logical and conceptual fluency and coherence, that is, we hope that people can better understand these topics by using human intelligence for the naming of the topics.

We did this by first coming up with a topic name using some of the keywords that actually make up a semantic meaning, and then seeing if the other "ignored" keywords are related to the initial topic name. For example, the representative key words of Topic 1 are: covid, emergency, medical, etc. It was thus named as "Emergency medical response", while the other words such as "analysis, measure" is found to be closely related to the response in practical application, showing relevance. Otherwise, the initial name needs to be adjusted and the whole process needs to be repeated until the relevance is found. The final names for each topic is listed in Table 2.

Table 2: Overview of the nine extracted topics

No.	Name	Definition	Main Topic Words
1	Emergency medical response	An emergency medical response to relieve medical stress in emergency situations.	covid, analysis, measure, security, emergency, medical, machine learning
2	Risk prediction	Prediction risk of mental disorders, treatment effects or future outcome of prognosis.	predict, risk, clinical, patients, psychosis, machine learning, symptoms
3	AI conversational intervention	Intervention of specific mental disorders by means of conversational communication.	chatbots, conversational, design, diagnosis, therapy, service, suicide, agencies
4	Future research directions	Future research and potential on clinical methods or treatment	review, study, clinical, methods, treatment, potential, social, future
5	AI performance analysis	Analysis of the performance of AI applications for prediction and diagnosis.	Feature, methods, predict, classification, accuracy, performance, algorithms, score
6	AI combining medical data	AI combines different medical data such as electroencephalogram, Nuclear magnetic resonance, etc. to intervene in mental health	brain, schizophrenia, control, psychosis, MRI, functional, image, sample
7	Student mental health prediction	Prediction on mental disorders among adolescents/ colleague students.	depression, students, stress anxiety, predict, emotion, college, network

8	Employee mental health measures	Measures of adults' anxiety, depression and other mental disorders.	distress, work, measure, physical, report, score, anxiety, depression
9	Community mental health	The impact of urban environmental factors on residents' mental health.	street, patient, residents, medical, urban, physical neighborhood

4.2 Topic Trend Analysis

The change in the popularity of topics is shown in Figure 4, where the topic order is sorted from high to low according to the overall heat. Before 2013, none of these topics are popular. However, after 2013, the popularities of all the topics begin to increase with different speeds. Growth in calculating the standard deviation (keep two decimal places), we got a group of data of 3.05, 2.29, 2.19, 1.87, 1.25, 1.93, 1.47, 1.54, 1.21 according to the topic order in figure 4. And taking the median of 1.87 as the threshold, we divided the nine topics into 2 types: rapidly growing topics and slowly growing topics.

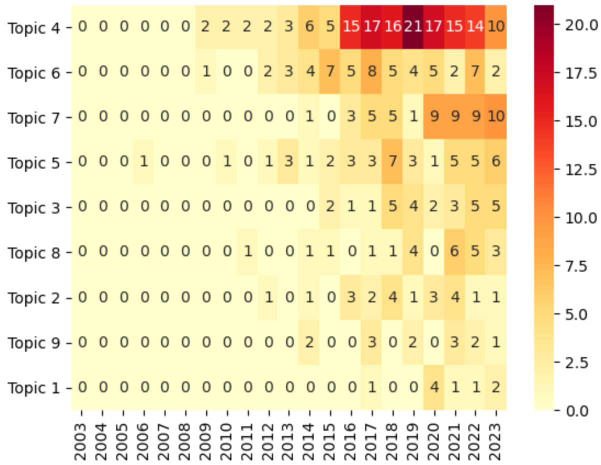

Figure 4: Heat map of topic evolution of AI articles

Rapidly Growing Topics

Topic 4 about the future research directions in the field of mental health topped the list of nine topics. The growth trend in the last 10 years is obvious. While AI technologies in supporting services in the mental health have shown promising results in many trials, there are many challenges in their real implementation phase (Torous et al., 2021). Just like the problem of privacy ethics, interpretability issues, the problem of chatbots' effectiveness on patients, and so on. Therefore, researchers are eager to find the direction of AI development in the field of mental health. It may be one of the reasons why Topic 4 research heat is at the top of the list.

Topic 5, AI performance analysis, deals with the performance metrics of their algorithms when using AI in the diagnosis, prediction of mental disorders. Its effectiveness when intervening in psychiatric disorders is tested through different perspectives such as new technological aspects of machine learning, robotics, deep learning and sensor-based systems (Khare et al., 2024). This can help us understand how AI systems perform in real-world applications, including accuracy, efficiency and reliability.

Topic 6, AI combining medical data, has gradually increased in popularity, ranking the second among the nine topics. The vast majority of research on this topic has directly analyzed medical data to intervene in mental disorders. For example, hybrid deep neural networks are developed based on EEG data for the classification of schizophrenia (Sun et al., 2021). Studies using AI to analyze medical images to discover effective biomarkers and then creating highly accurate diagnostic and efficacy prediction models (e.g., Li et al., 2020) have provided a new way for the applications of AI in the mental health field.

Topic 7, student mental health prediction, ranks 4th among the nine topics, which is in the upper middle range. This suggests that the mental health problems of the adolescent/ colleague student population are in urgent need of attention. As a result, research and literature focusing on this topic is increasing. As for students, they may often be reluctant to see a psychologist for a variety of reasons, such as shame, lack of relevant knowledge, poor financial conditions, or lack of family/social support. Therefore, AI algorithmic models combining data collected by wearable devices (Lekkas et al., 2023), social media texts (Ding et al., 2020), voice data and so on can help to intervene such a population segment more effectively. Using data from daily life is less intrusive for them than using the specialized medical data obtained in clinic or hospitals.

Topic 8 follows Topic 7, moving from students to another population, mainly employees. This topic involves the assessment of work stress to achieve early screening and intervention for mental disorders.

Slowly Growing Topics

Topic 1 on AI for emergency medical response was boosted during the COVID-19 pandemic when the demand for mental health services increased dramatically. AI automated diagnostic and therapeutic tools begins to emerge as an emergency medical response to alleviate the strain on healthcare resources in the past few years (Di Carlo et al., 2021). Although the epidemic is still a worldwide healthcare issue today, the urgency is not that high. Therefore, it is natural that the heat of this topic is fading, becoming stable.

The popularity of Topic 3, AI conversational therapy, has been rising gradually over the last decade. However, the current evidence supporting the effectiveness of chatbot interventions for various mental disorders is weak (Abd-Alrazaq et al., 2020). One of the main reasons is the lack of empathy compared to human counselors. The non-human nature of AI robots needs more attention and the concept of artificial empathy needs further research (Shao, 2023).

Topic 2, risk prediction with AI models, has been slowly gaining attention. But its overall heat among the nine topics is relatively low. The predictions cover almost all stages of disease development: pre-onset (Byeon, 2021), post-disease (Del Fabro et al., 2023) and prognosis (Molteni et al., 2019). Although these applications have begun to emerge, data for prediction of people at high risk are difficult to obtain and the black-box feature of AI models - lack of interpretability leads to the inability to inform the reasons for belonging to a high risk after prediction (Graham & Depp, 2019). These may all contribute to the slow growth of research buzz on this topic.

The development trend of Topic 9, community mental health, is also flat. This topic focuses on some external factors such as green spaces (Wang et al., 2019) that impact mental health. A more comprehensive understanding and implementation of these beneficial external factors can serve as a viable approach to prevent the onset of mental health disorders.

FUTURE WORK AND EXPECTED CONTRIBUTIONS

This study aims to fill in the current research gaps by reviewing the research on AI applications in mental health and proposing a two-staged method. The work-in-progress has extracted nine research topics and examined the evolution of these topics, which has contributed to the current literature with a whole picture of the research in the related area.

In future, we will select and review the relevant literature based on the nine research topics identified through the DTM model. This will help us to fully grasp the current status, trends and key challenges of AI in mental health services. With the two-staged strategy, we expect that this study can not only save time and labor invested in literature search, but also position the critical literature in a more effective way.

Secondly, we will further analyze the effect and reserve effect between AI applications and mental health needs. Collaborative optimization between technical systems and social systems can improve system performance (Davis et al., 2014). In our research field, this interdisciplinary cooperation is expected to provide theoretical support and practical guidance for its technical development and applications.

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