A Review of Personalized Recommender System for Mental Health Interventions

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***Abstract*—Personalized recommender systems for mental health are becoming indispensable instruments for providing individuals with individualized resources and therapeutic interventions. This study aims to explore the application of recommender systems within the mental health domain through a systematic literature review. The research is guided by three primary questions: 1) What is a recommender system, and what techniques are available within these systems? 2) What techniques and approaches are used explicitly in recommender systems for mental health applications? 3) What are the limitations and challenges in applying recommender systems in the mental health domain? The first step in answering these questions is to give a thorough introduction to recommender systems, covering all the different methods, including content-based filtering, collaborative filtering, knowledge-based filtering, and hybrid approaches. Next, examine the specific techniques and approaches employed in the mental health context, highlighting their unique requirements for adaptation, benefits, and limitations. Ultimately, the research highlights the key limitations and challenges, including data privacy concerns, the need for tailored recommendations, and the complexities of user engagement in mental health environments. By synthesizing current knowledge, this review provides valuable insights into the potential and constraints of recommender systems in supporting mental health, offering guidance for future research and development in this critical area.**

***Keywords*—Recommender system; collaborative filtering; content-based filtering; hybrid recommender system; mental health**

I. Introduction

Recommender systems, also called information filtering support, are used to predict or suggest an item, such as products, movies, content, and others, based on machine learning algorithms that the user might be interested in. It uses content-based filtering, collaborative filtering, and a hybrid recommender system to generate recommendations based on user preferences, behavior, and other relevant data. Today, recommendation systems have become the most popular tools for personalized support, and they have the potential to personalize mental health support further and improve treatment outcomes in the digital mental health landscape.

The area of mental health treatments has seen a significant change in recent years, with a focus on acknowledging the needs, preferences, and characteristics of those who are seeking help. One in three Malaysians have a mental disease, yet half of those diagnoses are erroneously raising concerns about mental health. Numerous mental health conditions are prevalent, such as anxiety, depression, bipolar disorder, schizophrenia, and more [1]. This shows that there is cause to be concerned and emphasizes the need for mental health support and education in Malaysia. While mental health interventions are essential for addressing people's well-being, the current field mainly uses long-standing, conventional methods, including clinical diagnosis and medication intervention [2]. Even while these traditional approaches are helpful, they have many limitations. The desire for personalization—where therapies can be customized to meet the unique needs of everyone—has been sparked by the realization that there is no one-size-fits-all approach to mental health care. This change reflects a broader understanding that individuals seeking help might benefit from more engaging, effective, and ultimately transformational mental health treatment.

The need for personalization in mental health interventions is becoming increasingly acknowledged, although a severe issue still exists. The way mental health treatment is now provided does not adequately allow therapies to be adapted to each patient's specific requirements. Although helpful, traditional methods might only fully utilize personalization's potential. This issue presents a significant difficulty since it might impair user engagement and satisfaction and, more importantly, the well-being of those who are seeking mental health help. Research on the effectiveness of recommender systems specifically designed for mental health therapies remains limited. The absence of robust empirical evidence makes it difficult to determine whether these approaches are beneficial and effective.

Thus, this study aims to conduct a systematic literature review on the application of recommender systems and their core techniques—including collaborative filtering, content-based filtering, knowledge-based filtering, and hybrid approaches—focusing specifically on their use in the mental health domain. It also seeks to compare these techniques, identifying their advances, challenges, and limitations associated with their implementation in this field.

II. Research Method

This paper offers an extensive systematic literature review that critically evaluates related works that pertain to the research topic. This dissertation's literature review mainly centers on diverse recommender systems that employ various recommendation techniques. These distinctions are organized and summarized in a tabulated format to enhance comprehension. The primary objective of this systematic literature review is to evaluate the methods available for crafting a recommender system that is ideally tailored for personalized mental health interventions.

A literature review is essential to research that comprehensively analyses existing literature on a particular topic. In the case of recommender systems, literature reviews are conducted to identify the current state of research, research trends, limitations, and opportunities. It also provides a guideline for future research in recommender systems. Hence, this part is essential to understand the current recommender systems research comprehensively. Conducting a systematic literature review (SLR) involves several key stages. Fig. 1 shows the critical stages in conducting a systematic literature review for this study.

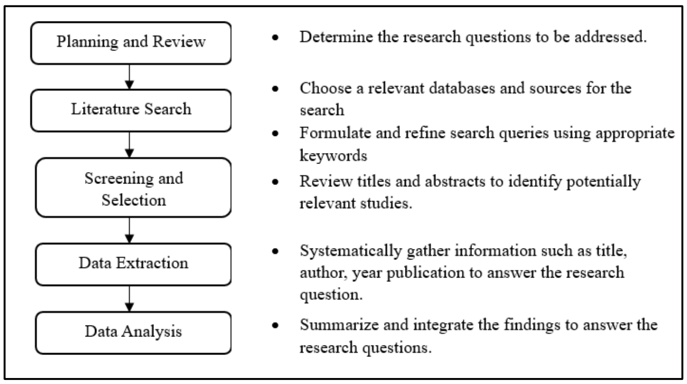

Fig. 1. Systematic literature review stage.

A. *Planning and Review*

This systematic review aims to understand the trends in recommender systems that can be effectively addressed, as well as the development and assessment of recommender systems. The research questions (RQ) aim to ascertain the limitations and difficulties associated with recommender systems and the evidence supporting their significance for individualized mental health. Below are the study questions that will be investigated during this comprehensive literature review:

- RQ1: What is a recommender system? What are the techniques available in the recommender system?
- RQ2: What techniques and approaches are used in recommender systems within the mental health domain?
- RQ3: What are the limitations and challenges in applying a recommender system for the mental health domain?

B. *Literature Search*

This section identifies relevant academic databases and sources well-regarded in personalized mental health recommender systems. Table I below shows an example of an academic database used to find relevant research in the field.

TABLE I. ACADEMIC DATABASE

Field	Academic Database
Recommender system	IEEE Xplore, ACM Digital Library, Scopus, and Google Scholar
Mental health interventions	PubMed.

The ultimate list of keywords was obtained after adding synonyms to make it longer. The search terms were defined using the research questions and the area's keywords as a guide. Table II presents examples of synonyms, and Table III presents a search query that was utilized for this study.

TABLE II. KEYWORD AND SYNONYM

Keyword	Synonym
Recommender	Suggestion, recommendation
System	Framework, mechanism, structure
Mental Health	Psychological health, emotional health, mental wellness
Intervention	Therapeutic support, support

TABLE III. SEARCH QUERY

Search ID	Search Term
S1	"Personalized recommender system" AND "mental health" AND "intervention"
S2	"Personalized recommendation for mental health" AND ("mental health intervention" OR "mental health therapeutic support")
S3	"Customized mental health interventions" AND ("recommender system" OR "recommendation system")
S4	("Personalized recommendation" OR "adaptive recommendation") AND ("mental health" OR "psychological health") AND ("intervention" OR "support")

C. *Screening and Selection*

In this activity, a few articles were selected to support the SLR. After identifying relevant papers, a quality assessment was conducted to avoid bias and internal and external validity. Incorporating the most recent research ensures that this SLR is current, comprehensive, and reflective of the state of the art in the application of recommender systems for mental health interventions. Therefore, only research published between 2019 and 2024 was chosen for this study. References were gathered, stored, and arranged using the desktop and web versions of the Mendeley software package.

About 612 results from the search were returned, comprising research articles, book chapters, proceeding papers, review articles, editorial materials, and early articles. After removing papers that were not relevant and adding relevant papers, 71) articles in total were used for this study. The flowchart below shows a detailed breakdown of the searched articles, as shown in Fig. 2.

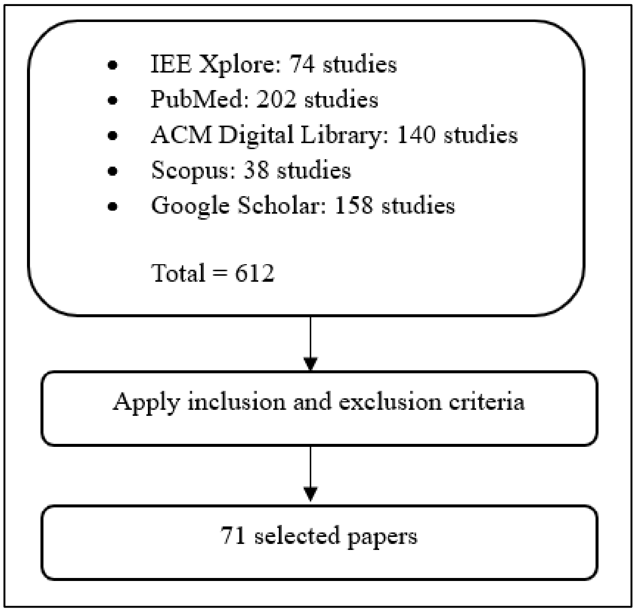

Fig. 2. Detailed breakdown of the searched articles

Explicit inclusion and exclusion criteria are necessary to guarantee that the studies are pertinent, excellent, and in line with the research goal. Table IV below shows the requirements for inclusion and exclusion.

TABLE IV. INCLUSION AND EXCLUSION

Inclusion	Exclusion
English article	Non-English article
Year published from 2019-2024	Outdated year publication
Related to the recommender system and mental health	Irrelevant to the studies
	Duplicate Literature

D. *Data Extraction*

Data extraction was carried out during the last phase of choosing primary research. Approaches, techniques, and application domains were among the crucial content data required to answer the research questions gathered, along with necessary metadata from the papers, such as author, title, and year of publication. Table V displays the framework for extracting data. First, a list of the extracted data is presented; next, any ambiguous data is clarified; finally, the research questions about the extracted information are explained in detail in the final column.

TABLE V. FRAMEWORK EXTRACTING DATA

Extract Data	Description	RQ
Author	Names of the authors of the study.	-
Title	Title of the study or paper	RQ1
Year of Publication	The year when the study was published	-
Journal/ Conference	Name of the journal or conference where the study was published.	-
Doi/ Link	Digital Object Identifier or URL for accessing the study	-
Application domain	Domain applied in the study	RQ2
Approach	Recommendation approach in the study	RQ3
Techniques	Technique applied in the study	RQ1

E. *Data Analysis*

For this review, 71 major research studies were dominated. From these studies, 23 journal articles, 26 conference papers, 4 workshop articles, 3 symposium articles, 4 handbook articles, and 11 others (website, review paper, etc.) were classified. The percentages of collated studies are presented in Fig. 3. In contrast, the total paper issued per year is presented in Fig. 4. This section presents the findings from a selection of studies that addressed each research question; these findings span several categories and include approaches, techniques, evaluation methodologies, and other crucial information.

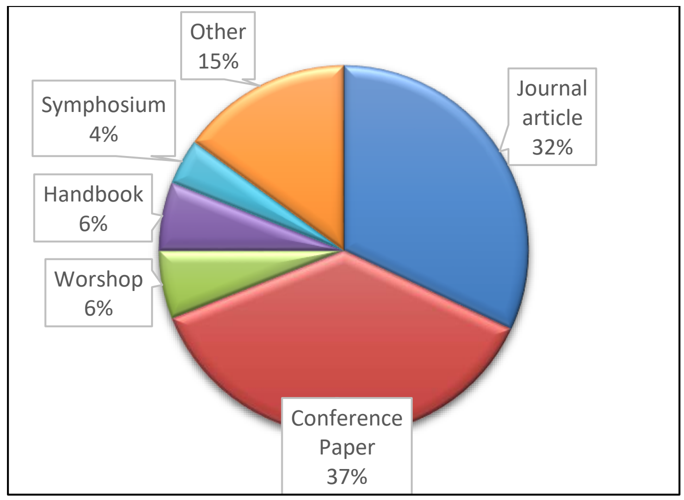

Fig. 3. Percentage of collated studies

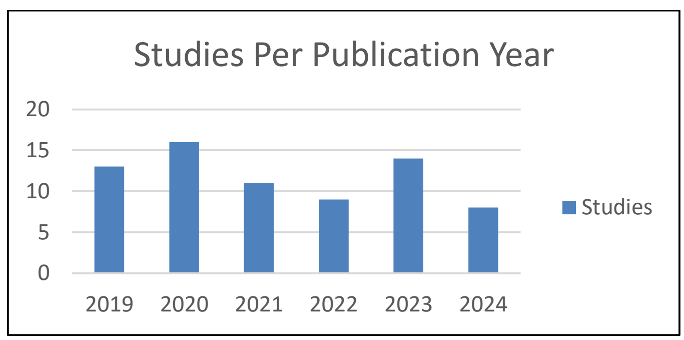

Fig. 4. Distribution of studies per publication year

III. REVIEW RESULT

A. *Review Result Based on Research Question*

1) Research question 1: What is a recommender system? What are the techniques available in the recommender system?

The rapid expansion of digital data and the growing number of internet users have led to the possibility of information overload, making it difficult for users to access relevant content on the web quickly. As a result, users often struggle to find the information they need promptly, leading to frustration and decreased engagement with online services. This problem is particularly acute for users looking for highly specific or niche content, as they may have difficulty finding relevant items in the vast sea of available information. To address this challenge, recommender systems have been developed to help users find relevant and valuable content based on their past behaviors and preferences.

A recommender system is an information filtering system that predicts the preferences or interests of a user and recommends items that the user may like. It is widely used in e-commerce, social media, and entertainment industries to provide personalized recommendations to users [3]. Studies from [4] state that recommender systems have become more sophisticated in recent years with the development of deep learning algorithms and large datasets. Today, recommender systems are used in various applications, such as Netflix, which suggests movies based on the user's previous viewing history; YouTube recommends videos or tracks based on the user's search history; and Amazon suggests additional products based on the user's purchase history. Similarly, Facebook recommends that people befriended based on the user's social network. Traditional recommender systems use different approaches to make recommendations to users. These approaches include content-based filtering, collaborative filtering, hybrid methods, and other techniques that can be classified into more categories, such as knowledge-based filtering [4].

The area of mental health treatments has seen a significant change in recent years, focusing on acknowledging the particular needs, preferences, and characteristics of those seeking help. One in three Malaysians have a mental disease, yet half of those diagnoses are erroneously raising concerns about mental health. Numerous mental health conditions are prevalent, such as anxiety, depression, bipolar disorder, schizophrenia, and more [5]. This shows that there is cause to be concerned and emphasizes the need for mental health support and education in Malaysia. While mental health interventions are essential for addressing people's well-being, the current field mainly uses long-standing, conventional methods, including clinical diagnosis and medication intervention [2]. Even while these traditional approaches are helpful, they have a lot of limitations. The desire for personalization—where therapies can be customized to meet the unique needs of each individual—has been sparked by the realization that there is no one-size-fits-all approach to mental health care. This change reflects a broader understanding that individuals seeking help might benefit from more engaging, effective, and ultimately transformational mental health treatment.

Thus, by utilizing recommender systems, which have become valuable instruments in the more significant healthcare industry, data-driven solutions that can improve personalized treatment are provided. These systems employ user data and algorithms to offer suggestions to enhance user experiences and healthcare service delivery. While this usage offers convenience, some disadvantages need to be addressed. Therefore, this study uses a hybrid recommendation system that combines several recommendation techniques, such as content-based filtering, collaborative filtering, knowledge-based filtering, and hybrid approach, which may overcome the problems and provide more accurate and diverse recommendations.

a) Collaborative filtering approach: Recommender systems use a technique called Collaborative Filtering (CF) to forecast a user's interests based on the tastes of users who are similar to the said user [6]. It is predicated on the notion that individuals who share a joint assessment of a given item will likely do so in the future. User-based and item-based CF are the two primary categories of CF. While item-based CF suggests products comparable to those a user has previously liked, user-based CF suggests items to a user that similar users have previously liked [7].

As to [8], user-based CF is a method that forecasts the items a user would find appealing by analyzing the ratings that other users with comparable tastes have assigned to that item. This kind of recommendation system bases its product recommendations on user similarities. On e-commerce platforms, this technique is frequently used to make product recommendations to consumers based on their browsing and past purchases. To suggest movies, TV series, and songs to customers based on their viewing or listening history is also utilized by streaming services like Netflix and Spotify [9].

Item-based CF is a subset that makes recommendations to consumers based on how two comparable items are determined by utilizing user ratings. [10] states that Amazon utilized and invented it in 1998, which has been essential to the company's success. Item-based CF examines the relationship between the two items and combines the user's rated and bought items with related goods to generate a suggestion list.

Hence, CF can be classified as a powerful tool for personalizing users' experiences and increasing customer engagement and satisfaction. Table VI below shows several advantages and disadvantages of CF recommendation approaches for recommending items.

TABLE VI. ADVANTAGES AND DISADVANTAGES OF COLLABORATIVE FILTERING APPROACH

Advantage	Disadvantage
Personalization: CF provides users with personalized recommendations based on their past behavior, preferences, and activities [11].	Cold start problem: CF has a cold start problem, in which it isn't easy to make recommendations for new users or items without ratings [12].
Diversity: CF can recommend items that are not popular, which can increase the diversity of recommendations and expose users to new items [12].	Sparsity: CF can suffer from sparsity, where there are not enough ratings or data points to make accurate recommendations [12].
Scalability: CF can handle large datasets and many users, making it scalable for e-commerce platforms and other applications [11].	Over-specialization: CF can lead to over-specialization, where users are recommended items that are too similar to their past behavior, limiting their exposure to new items [12].
Adaptability: CF can adapt to user interest and preference changes over time, making it a dynamic and flexible recommendation system [11].	Popularity bias: CF can suffer from popularity bias, where popular items are recommended more frequently, leading to a need for more diversity in recommendations [11].

b) Content-based filtering approach: In recommender systems, content-based filtering (CBF) is a technique that uses the user's attributes to forecast and suggest new but comparable things [13]. The more a consumer participates, the more accurate future suggestions are generated by the CBF algorithm, which retains past user data, including clicks, reviews, and favorites, to establish a user profile. The author in [14] claims that this method does not use the data of other users when making suggestions to a single user; instead, it attempts to infer a user's features or behavior based on the item's features. Each item's unique traits must reflect its fundamental characteristics when using CBF. For example, the recommender system requires specific movie attributes, including actors and actresses, directors, the year of release, and genre, to discriminate between movies [15].

According to a [18] publication, the CBF model finds similarities between things to make suggestions based on specific criteria. These systems generate data profiles by utilizing description information, which could comprise attributes of objects or individuals. The users who previously liked, purchased, viewed, or listened to products are then suggested to them based on the developed profiles. The premise is that people may enjoy similar goods in the future if they have previously liked specific items, which is crucial to content-based filtering.

Two common approaches are typically employed in content-based filtering: Cosine distance and classification [13] [17]. In the cosine distance method, the cosine distance between the user and item vectors determines preference. For instance, the action movie vector has a positive value for a user who enjoys watching it, but the horror movie vector has a negative value for that same person. The cosine distance is used to find the similarity between the user and item vectors, and the items with the highest similarity score are recommended for use [13] [18]. The classification approach method uses a classification algorithm to predict whether a user will like an item or not based on the item's features; for example, a decision tree algorithm can be used to predict whether a user will like a movie based on its genre, director, actors, and other features. The algorithm learns from the user's past preferences and creates a model that can predict the user's future preferences [13] [18].

In summary, CBF is a method for recommender systems that uses machine learning algorithms to forecast and suggest new but comparable items based on those attributes to the user. The more a consumer participates, the more accurate future suggestions are generated by the CBF algorithm, which retains past user data, including clicks, reviews, and favorites, to establish a user profile. Rather than focusing on how an object interacts with the user, CBF approaches need additional information about its features. Table VII below shows several advantages and disadvantages of CBF recommendation approaches for recommending items.

TABLE VII. ADVANTAGES AND DISADVANTAGES OF CONTENT-BASED FILTERING

Advantage	Disadvantage
No-item cold-start problem: Content-based filtering can recommend items to new users who have yet to have any interaction [19].	Limited capacity to build upon users' current interests: The model can only provide recommendations based on the user's current interests. It is not able to build upon those interests [19].
Scalability: Since the recommendations are unique to this person, the model does not require any information about other users, simplifying scaling to many users [19].	Needs extensive domain expertise: Because the item feature representation is partially hand-engineered, this technique calls for a great deal of subject knowledge [19].
Recommendations for niche products: Based on the user's preferences, the model can identify products that only a tiny percentage of users are interested in [19].	Limited quality consideration: Content-based filtering systems mostly need to consider the quality of the items in the recommendation process [20]

c) Knowledge-based filtering approach: The knowledge-based filtering (KBF) approach is a recommendation system that does not rely on user data or ratings but instead uses domain knowledge to make recommendations. KBF systems use a set of rules or knowledge to recommend items to users based on their preferences [21][23].

According to [22], KBF systems are often used in domains where domain knowledge is readily available, such as the medical field or in recommending books. However, the quality and completeness of their domain knowledge need to be improved.

In summary, the knowledge-based filtering approach is a recommendation system that uses domain knowledge to make recommendations. It does not rely on user data or ratings, can explain its recommendations, and can handle new items. However, it is limited by the quality and completeness of its domain knowledge; it can only recommend items that match the user's known preferences and acquiring domain knowledge can take time and effort. Table VIII below shows several advantages and disadvantages of KBF recommendation approaches for recommending items.

TABLE VIII. ADVANTAGES AND DISADVANTAGES OF KNOWLEDGE-BASED FILTERING

Advantage	Disadvantage
No need for user data: Knowledge-based filtering systems do not require user data or ratings, making them useful when user data is unavailable [21][2].	Limited to domain knowledge: Knowledge-based filtering systems are limited by the quality and completeness of their domain knowledge [22].
Able to offer clarifications: Knowledge-based filtering systems can make their recommendations more visible and understandable by providing justifications for them [22].	Limited to known preferences: Knowledge-based filtering systems can only recommend items that match the user's known preferences and cannot expand on the user's interests [23].
Can handle new items: Knowledge-based filtering systems can handle new items that have yet to be rated by users [23].	Difficulty in acquiring domain knowledge: Acquiring domain knowledge can be challenging and time-consuming [22].

d) Hybrid recommender system approach: Hybrid recommender systems integrate the complementary qualities of two or more recommendation algorithms differently to benefit from the complementary qualities of two or more recommendation algorithms. Combining two or more recommendation algorithms, hybrid recommendation systems seek to give users more accurate, varied, and well-balanced recommendations. [24][25].

Developing hybrid recommender systems by fusing various methods, like content-based and collaborative filtering, is possible. While the content-based filtering component considers objects' particular characteristics and properties, the collaborative filtering component gathers the general public's knowledge [25][26]. According to an article by [24], there are various kinds of hybrid recommender systems, such as feature combination hybrid, weighted hybrid, switch hybrid, and mixed hybrid.

In summary, hybrid recommender systems leverage the complementary advantages of two or more recommendation algorithms by combining them in diverse ways. They can offer better coverage of the item space, overcome the shortcomings of individual methodologies, and deliver more precise recommendations. Nevertheless, choosing the best mix of approaches can take time and effort, and they might be more challenging to develop and maintain than single-technique systems. They also require more data. Different techniques, such as collaborative and content-based filtering, can be combined to create hybrid recommender systems. Table IX below shows several advantages and disadvantages of the hybrid recommender system approach in recommending items.

TABLE IX. ADVANTAGES AND DISADVANTAGES OF HYBRID RECOMMENDER SYSTEM

Advantage	Disadvantage
Overcoming limitations of individual techniques: Hybrid recommender systems can combine individual techniques to overcome their limitations [25].	Complexity: Hybrid recommender systems can be more complex to implement and maintain than single-technique systems [25].
Increased accuracy: Hybrid recommender systems can produce more accurate recommendations by integrating the advantages of several strategies [27].	Data requirements: Hybrid recommender systems require more data than single-technique systems [25].
Better coverage: Hybrid recommender systems can combine different techniques to provide better coverage of the item space [24].	Difficulty in selecting the right combination of techniques: Selecting the right combination of techniques can be challenging, and the hybrid system's performance depends on the quality of the individual methods [24].

2) Research question 2: What techniques and approaches are used in recommender systems within the mental health domain?

Recommender systems can improve the user experience of mental health apps by personalizing the intervention, making it more applicable to the needs of the individual user and, thus, more engaging [28] [29]. Through personalized recommendations, these systems can effectively customize the content, resources, and interventions offered by mental health apps, creating a more tailored and relevant experience for each user. According to [29], recommender systems can filter content and provide tailored mental health suggestions by leveraging individual usage data. Through meticulous analysis of user behavior, preferences, and interactions within mental health apps, these systems can discern patterns and preferences unique to each user. This insightful data analysis enables recommender systems to curate personalized content, ensuring that mental health suggestions are finely tuned to match the specific needs and interests of the individual.

Other than that, the recommender system for mental health personalization represents a transformative approach in mental health care, enabling the adaptation of treatments to the unique needs of individuals and thereby enhancing the overall care for depressive symptoms and beyond [30]. By customizing therapeutic strategies based on a person's specific circumstances, preferences, and responses, these interventions can optimize the effectiveness of treatment. According to [31], content recommendation systems are pivotal in scaling and complementing digital mental health care by offering personalized content and self-care recommendations. These systems leverage advanced algorithms to analyze user data, preferences, and behaviors, tailoring the delivery of relevant resources to individuals seeking mental health support.

Therefore, recommender systems can transform the mental health care field by personalizing interventions and better tailoring them to specific users' needs. They can be applied in various ways in mental health apps to ascertain what would be pertinent to the user. They use algorithms to forecast material or information relevant to the user.

a) Collaborative filtering for mental health: A CF Recommender System for Mental Health technology uses algorithms to provide personalized recommendations for mental health treatments or interventions. This system is designed to enhance the personalization of mental health care by recommending treatments or interventions based on the similarities between patients and their responses to different treatments. According to [22], CF algorithms, such as matrix factorization and k-nearest neighbors, have been used to improve the personalization of digital mental health therapy. These algorithms have shown a 6.5-8.3% improvement in treatment personalization.

The system uses patient ratings of treatment efficacy and demographic data to recommend treatments to new patients. Based on shared demographic and behavioral traits, it groups users into clusters. The model may suggest a treatment for a patient who is entirely new to the model or has taken depressive therapies in the past by comparing and classifying users based on specified demographic similarities and comparing treatments based on efficacy rating similarities across users [32].

Furthermore, [33] points out that CF can suggest places and activities that, according to users' prior experiences, may have a greater chance of having a favourable impact. With this, users may find tiny moments of thankfulness and joy in their daily lives. Recommended systems for digital mental health apps have some ethical concerns, especially for those that employ artificial intelligence and personal data. These include concerns about privacy, personalization trade-offs, explainability, and the calibre of recommendations [22].

In summary, by tailoring interventions to the specific needs of each user, CF Recommender Systems for Mental Health has the potential to transform the way mental health care is provided completely. However, these systems' efficacy depends on the quantity and calibre of data available, and their application necessitates careful consideration of moral dilemmas.

b) Content-based filtering for mental health: A CBF Recommender System for Mental Health is a technology that uses algorithms to provide personalized recommendations for mental health treatments or interventions based on individual usage data. This system is designed to enhance the personalization of mental health care by recommending treatments or interventions based on the individual's past behavior and preferences. The author in [29] claim that CBF approaches have great potential for offering individualized mental health advice. Based on a user's personal information and past usage statistics, these strategies employ information filtering algorithms to provide suggestions or recommendations for appropriate material.

Therefore, by tailoring interventions and making them more relevant to the needs of specific users, CBF Recommender Systems for Mental Health have the potential to transform the way that mental health care is provided completely. However, the quality and availability of data determine how effective these systems are and using them requires careful ethical considerations [29].

Unfortunately, minimal research has been conducted in this area, possibly due to several reasons, including the sensitive nature of mental health data and the recent emergence of technology-driven solutions. It is possible that this area of study is still emerging or that research in this specific niche needs to be expanded.

c) Hybrid recommender system for mental health. A hybrid recommender system for mental health combines multiple recommendation approaches to provide individuals with personalized mental health support and resources. Research by [33] about a hybrid recommender system for mental illness detection in social media using deep learning techniques mentions that a hybrid recommender system is a sophisticated tool that combines various algorithms to analyze social media data and identify potential signs of mental illness. This system is primarily designed to optimize the detection of mental health issues, particularly depression, by analyzing patterns in social media behavior and content.

However, while hybrid recommender systems have demonstrated their potential in various domains, there is a notable lack of research specifically focused on their application in mental health. Technology plays a crucial role in mental health support, so developing hybrid recommender systems can contribute to more effective, accessible, and user-centric mental health care.

3) Research Question 3: What are the limitations and challenges in applying a recommender system for the mental health domain?

The sensitive nature of mental health data and the complexity of individual needs make the application of recommender systems in the mental health domain complex and fraught with limitations. Technological, data science, ethics, and mental health specialists must collaborate to address these issues multidisciplinary. Table X below shows the constraints and challenges in several studies on the recommender system approach using the CBF technique, CF technique, and hybrid recommender system in the mental health domain.

TABLE X. SUMMARIZATION OF RECOMMENDER SYSTEM FOR MENTAL HEALTH DOMAIN

Recommender System Approach	Studies	Limitation and challenge
CBF Technique	[29]	The lack of explainability in recommender systems used in DMH apps raises ethical concerns.
CF Technique	[27]	The analysis does not consider the cold-start scenario, in which the algorithms predict for users something they have never seen before, which is a well-known challenge for recommender systems.
	[31]	● User cold-start problem: User-user collaborative filtering relies on finding similarities in item ratings between users to make recommendations. However, a cold-start user with no item ratings cannot be given a recommendation. ● The sparsity of data: If users have rated only a few items, similarity measures between users become unreliable, affecting the accuracy of recommendations.
	[32]	There are challenges in developing engaging and personalized digital interventions, the potential of recommender systems to address these challenges, and the need for further research and empirical evaluation.
Hybrid Recommender System	[33]	Requires large labelled social media datasets, which can be difficult to obtain

IV. DISCUSSION

Specific gaps and limitations have been evident in the recommender systems literature, pointing to areas where further exploration and development are warranted. One of the primary challenges is the availability and quality of the data. Recommendation algorithms may not be as successful when dealing with sparse or noisy mental health data, such as user preferences, behavior patterns, and treatment results. To address this issue, data are collected through an online platform, which offers users the most accessible means to contribute and receive recommended interventions from the system. Experts in the field of mental health provide these intervention data. Using an online platform to collect data and incorporating the expertise of mental health professionals could help alleviate some of the difficulties associated with limited or unreliable mental health data. However, it is essential to recognize that these approaches may not eliminate all problems. Nevertheless, they have the potential to significantly improve the quality, relevance, and effectiveness of the system's proposed mental health therapies.

Furthermore, it is crucial to acknowledge the limited research on recommender systems designed for mental health treatments. Prior research in this field often utilizes several recommendation strategies, demonstrating a wide array of methodologies. Yet, these methods have their inherent restrictions and difficulties. While hybrid recommender systems have the potential to tackle some obstacles, there is still a lack of research on their use in mental health settings. Although hybrid recommender systems have the potential to be effective in the field of mental health intervention, more research is required to evaluate their practicality, effectiveness, and implementation. The potential for synergies in hybrid recommender systems still needs to be explored. Focusing only on specific methods can make it harder to understand hybrid approaches, which could mean missing chances to improve the quality of recommendations.

Moreover, consistency in evaluating metrics across studies presents challenges in comparing and benchmarking recommender system performance. Standardized metrics and benchmarks are lacking, making it difficult to establish a common framework for evaluating recommendation quality. Addressing this requires the adoption of standardized metrics and benchmarks for more equitable comparisons.

A common challenge in recommender systems is the "cold start" problem, where recommender systems struggle to make practical recommendations for new users or items with limited data. Many studies need to adequately address this issue, which can lead to suboptimal recommendations for newcomers. Solving this problem is essential to ensure valuable recommendations for all users. In this case, combining a few techniques, which are CF, CBF, and KBF, may leverage the strengths of each approach to overcome the limitations of individual methods and handle the cold start problem more effectively.

In conclusion, it is essential to identify these holes and problems in the literature on recommender systems and take action so that the field can continue to grow and recommendation technologies improve. Future research on these areas will contribute to advancing recommender systems and their ability to serve diverse user needs and preferences.

V. Conclusion

This paper comprehensively explores recommender systems, focusing on enhancing personalization. Recommender systems are central in personalizing recommendations across various domains, improving user experiences, and guiding choices. Traditional approaches like CF and CBF are commonly used but have limitations, including the cold start problem and difficulty capturing diverse user preferences. There are challenges in delivering personalized care, including privacy concerns, the need for real-time recommendations, and limitations in cross-domain recommendations. Hence, hybrid recommender systems, which combine various recommendation techniques, hold promise for overcoming the limitations of traditional methods.

Evaluating recommender systems is essential, and standardized metrics and benchmarks are necessary for fair assessments. User and intervention data should be integrated into the evaluation of the recommendation system. Additionally, interpretability and explainability of recommendations are critical to building user trust and engagement. Privacy and ethical considerations, including data misuse and user profiling, should be considered to ensure responsible data use.

To wrap up, this review provides valuable insights into the world of recommender systems, their challenges, and the potential for improvement. The review emphasizes the importance of addressing gaps and limitations to create more effective and ethical recommendation systems that meet users' diverse needs and preferences.

VI. Future Work

Insights from the literature review suggest several promising directions for future research in recommender systems for mental health therapies. These directions are essential for overcoming current limitations and advancing the development of practical, user-friendly, and ethically sound recommendation technologies in mental health care.

Future work should prioritize addressing key challenges, including improving recommendation accuracy, mitigating cold start and data sparsity problems, and upholding ethical standards in system design and deployment. Enhancing the personalization of recommendations by integrating contextual factors such as user preferences, emotional states, and mental health history could significantly improve system performance. Moreover, innovative approaches to data utilization, such as incorporating external data sources and leveraging hybrid models, could help alleviate data-related limitations.

Research should also focus on evaluating the real-world efficacy of these systems through longitudinal studies and clinical trials to better understand their impact on mental health outcomes. Additionally, expanding the applicability of recommender systems to diverse populations is crucial for ensuring inclusivity and addressing cultural, demographic, and individual differences in mental health needs.

Exploring advanced techniques, such as deep learning, reinforcement learning, and multimodal data integration, offers further opportunities to push the boundaries of current methods. By investigating these areas, future research can significantly contribute to developing more accurate, portable recommender systems that align with ethical considerations and user needs.

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References

[1] Mental health in Malaysia: Overcoming stigma and benefits of improving access to care. Mental Health Malaysia: Overcoming Stigma |

Prudential Malaysia. (n.d.). https://www.prudential.com.my/en/we-do-pulse/all-stories/mental-health-malaysia/

[2] Siddiqui, S., Morris, A., Ikeda, D. J., Balsari, S., Blanke, L., Pearsall, M., Rodriguez, R., Saxena, S., Miller, B. F., Patel, V., & Naslund, J. A. (2022). Scaling up community-delivered mental health support and care: A landscape analysis. Frontiers in public health, 10, 992222. https://doi.org/10.3389/fpubh.2022.992222

[3] Kim, J., & Lee, J. (2021). The Impact of Accuracy and Diversity on Customer Satisfaction with Recommender Systems. Journal of Information Science Theory and Practice, 9(2), 1-14.

[4] Sharma, S., Gupta, K., & Gupta, D. (2021). Recommender System: A bibliometric analysis. In IOP Conference Series: Materials Science and Engineering (Vol. 1022, No. 1, p. 012057). IOP Publishing.

[5] Mahtar, S.N.A.M., Masrom, S., Omar, N., Khairudin, N., Rahim, S.K.N.A. and Rizman, Z.I. (2017). Trust-aware recommender system with distrust of different views of trusted users. Journal of Fundamental and Applied Sciences, 9(5S), pp.168-182.

[6] 7Gupta, S. (2019, April 1). Collaborative filtering and embeddings - part 1. Medium. https://towardsdatascience.com/collaborative-filtering-and-embeddings-part-1-63b00b9739ce

[7] [8] Ajitsaria, A. (2022). Build a recommendation engine with collaborative filtering, Real Python. Available at: https://realpython.com/build-recommendation-engine-collaborative-filtering/ (Accessed: 23 June 2023).

[8] Gupta, R. (2023, January 22). User-based collaborative filtering. GeeksforGeeks. https://www.geeksforgeeks.org/user-based-collaborative-filtering/

[9] Konduforov, A. (2021, July 27). Recommender systems: Behind the scenes of machine learning-based personalization. AltexSoft. https://www.altexsoft.com/blog/recommender-system-personalization/

[10] Qutbuddin, M. (2023, September 3). A comprehensive guide on Item Based Recommendation Systems. Medium. https://towardsdatascience.com/comprehensive-guide-on-item-based-recommendation-systems-d67e40e2b75d

[11] Holewa, K. (2020, June 29). We know what you like! Perks of recommendation systems in business. Medium. https://medium.com/swlh/we-know-what-you-like-perks-of-recommendation-systems-in-business-5f227bb6d09

[12] Skovhøj, F. Z. (2022, February 9). Using collaborative filtering in e-commerce: Advantages & disadvantage. Clerk.io. https://www.clerk.io/blog/collaborative-filtering

[13] Turing Enterprises Inc. (2022, August 5). A guide to content-based filtering in Recommender Systems. A Guide to Content-based Filtering in Recommender Systems. https://www.turing.com/kb/content-based-filtering-in-recommender-systems

[14] Roy, A. (2020, July 31). Introduction to Recommender systems- 1: Content-based filtering and collaborative filtering. Medium. https://towardsdatascience.com/introduction-to-recommender-systems-1-971bd274f421

[15] Castells, P. and Jannach, D. (2023). Recommender Systems: A Primer. arXiv preprint arXiv:2302.02579.

[16] AltexSoft. (2021, July 27). Recommender systems: Behind the scenes of machine learning-based personalization. AltexSoft. https://www.altexsoft.com/blog/recommender-system-personalization/

[17] The Upwork Team. (2021, April 6). What content-based filtering is & why you should use it | upwork. https://www.upwork.com/resources/what-is-content-based-filtering

[18] Leban, J. (2020, May 21). Essentials of recommendation engines: Content-based and collaborative filtering. Medium. https://towardsdatascience.com/essentials-of-recommendation-engines-content-based-and-collaborative-filtering-31521c964922

[19] Google. (n.d.). Collaborative Filtering Advantages & disadvantages | machine learning | Google for developers. Google. https://developers.google.com/machine-learning/recommendation/collaborative/summary

[20] Lops, P., Jannach, D., Musto, C., Bogers, T., & Koolen, M. (2019). Trends in content-based recommendation: Preface to the special issue on Recommender systems based on detailed item descriptions. User Modeling and User-Adapted Interaction, 29, 239-249.

[21] Nießner, J., & Ludwig, T. (2021). Design of a knowledge-based recommender system for recipes from an end-user perspective. Mensch Und Computer 2021. https://doi.org/10.1145/3473856.3473888

[22] Markchom, T., Liang, H., & Ferryman, J. (2023). Scalable and explainable visually-aware Recommender Systems. Knowledge-Based Systems, 263, 110258. https://doi.org/10.1016/j.knosys.2023.110258

[23] Chicaiza, J., & Valdiviezo-Diaz, P. (2021). A comprehensive survey of knowledge graph-based recommender systems: Technologies, development, and contributions. Information, 12(6), 232. https://doi.org/10.3390/info12060232

[24] Çano, E. and Morisio, M. (2017). Hybrid recommender systems: A systematic literature review. Intelligent Data Analysis, 21(6), pp.1487-1524.

[25] Kharwal, A. (2023, June 5). Hybrid recommendation system using Python: Aman Kharwal. thecleverprogrammer. https://thecleverprogrammer.com/2023/06/05/hybrid-recommendation-system-using-python/

[26] Lineberry, A. (2018, September 11). Creating a hybrid content-collaborative movie recommender using Deep Learning. Medium. https://towardsdatascience.com/creating-a-hybrid-content-collaborative-movie-recommender-using-deep-learning-cc8b431618af

[27] Parks, J. (2023, April 27). How to Build a Hybrid Recommender System. How to build a hybrid recommender system. https://agilethought.com/blogs/how-to-build-hybrid-recommender-system/

[28] Lewis, R. et al. (2022) 'Can a recommender system support treatment personalisation in Digital Mental Health therapy? A quantitative feasibility assessment using data from a behavioural activation therapy app,' CHI Conference on Human Factors in Computing Systems Extended Abstracts [Preprint]. doi:10.1145/3491101.3519840.

[29] Valentine, L., D'Alfonso, S. and Lederman, R. (2022). Recommender systems for mental health apps: advantages and ethical challenges. AI & Society, pp.1-12.

[30] Hornstein, S., Zantvoort, K., Lueken, U., Funk, B., & Hilbert, K. (2023). Personalization strategies in digital mental health interventions: A systematic review and Conceptual Framework for depressive symptoms. Frontiers in Digital Health, 5. https://doi.org/10.3389/fdgth.2023.1170002

[31] Chaturvedi, A., Aylward, B., Shah, S., Graziani, G., Zhang, J., Manuel, B., Telewa, E., Froelich, S., Baruwa, O., Kulkarni, P. P., Ξ, W., & Kunkle, S. (2023). Content Recommendation Systems in Web-Based Mental Health Care: Real-world Application and Formative Evaluation. JMIR formative research, 7, e38831. https://doi.org/10.2196/38831

[32] Orlando, A., Venuti, K., & Tesfalul, M. (n.d). Collaborative Filtering Recommender System for Treatment of Depression.

[33] Siriaraya, P., Suzuki, K., & Nakajima, S. (2019, September). Utilizing Collaborative Filtering to Recommend Opportunities for Positive Affect in daily life. In HealthRecSys@ RecSys (pp. 2-3).

[34] Ahmad, S. S., Rani, R., Wattar, I., Sharma, M., Sharma, S., Nair, R., & Tiwari, B. (2023). Hybrid recommender system for mental illness detection in social media using deep learning techniques. Computational Intelligence and Neuroscience, 2023(1), 8110588.