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Overview of chatbot usage on mental health: a scoping review

Ririn Indah Permatasari[1]*, *Dian* Parama Artha[1], *Bayu* Satria Wiratama[1,2], *Hanifah* Wulandari[1,2]

[1] Master of Public Health Program, Faculty of Medicine, Public Health, and Nursing, Universitas Gadjah Mada, Yogyakarta 55281, Indonesia
[2] Department of Biostatistics, Epidemiology, and Population Health, Faculty of Medicine, Public Health, and Nursing, Universitas Gadjah Mada, Yogyakarta 55281, Indonesia

Abstract. Mental disorders have become the second most significant global health burden. One approach to reducing the medical and socio-economic impacts of mental illnesses/disorders is leveraging the power of digital health technology. Chatbots, in particular, hold great potential for providing social and psychological support, akin to human interactions. This research aims to map the use of mental health chatbot technology using the scoping review method based on the Preferred Reporting Items for Systematic Reviews and Meta-Analyses Extensions for Scoping Reviews. The results are categorized according to use, including acceptability, effectiveness, usability, adoption, and features. Study selection was assisted by Rayyan. Data extraction used a narrative approach. Chatbots were classified based on purpose, target population, targeted mental health disorders, and usage metrics. 21 out of 172 research articles met the inclusion criteria. Anxiety, depression, and stress were the most common target disorders for chatbot use, although a combination of focuses is quite ideal for mental health chatbots. Many chatbots have been used for various types of mental disorders. Their purposes range from prevention and training to therapy, with most being a combination. Further research is needed to understand the changes that occur following interventions using mental health chatbots.

1 Introduction

Mental disorders are one of the leading causes of disability worldwide, according to data on years lost due to disability (YLDs) conducted by the Global Burden of Disease Study in 2019 by The Institute for Health Metrics and Evaluation (IMHE) on the global burden of disease. Mental disorders are the second largest health burden globally for adolescents (15-19 years) and the third for the productive age group (20-39 years). Geographically, mental disorders account for 14.59% of disabilities worldwide, 13.08% of disabilities in Indonesia, and 11.79% of disabilities in Yogyakarta. Mental disorders are also a major risk factor for suicidal behavior or intent [1].

Mental health issues have been frequently discussed since the pandemic and into the post-pandemic period. One approach to reducing the medical and socio-economic impacts of

*Corresponding author : ririnindahpermatasari@mail.ugm.ac.id

mental illnesses/disorders is leveraging the power of digital health technology to provide assistance, prevention, and therapy solutions to improve mental health. Digital Mental Health is defined as any application of digital health technology for the assessment, support, prevention, and treatment of mental health [2].

The use of digital mental health services has skyrocketed since the beginning of the COVID-19 pandemic, particularly among those who had already utilized face-to-face mental health services. Funding for digital mental health startups grew by 79% in 2021 [3]. However, in its development, digital mental health services are often implemented without adequate steps for acceptance and feasibility [4]. One type of digital mental health service is in the form of a chatbot. Chatbots have great potential in offering social and psychological support, similar to human interactions in the real world. This technology allows individuals to connect with friends or family members or seek professional support [5].

Recently, research on mental health chatbots has become quite prevalent, especially those discussing their use in terms of acceptability, effectiveness, usability, adoption, features, and user engagement [6]. Adequate steps for acceptance and feasibility are important for implementing the usefulness of chatbots in mental health. This research aims to explore, categorize, and identify the characteristics of the use of various existing chatbots.

2 Materials and Methods

We conducted a review of research related to chatbots used for mental health. We followed the Preferred Reporting Items for Systematic Review and Meta-Analysis (PRISMA, Figure 1) as a guideline for carrying out the scoping review. Study selection was assisted by Rayyan to improving the reliability of the selection and data extraction process. This helps to resolve disagreements between reviewers and ensures that a consensus is reached on the inclusion of each study.

2.1 Search Strategy

Table 1. Literature Search Strategy

Database	Keywords	Number of Studies
Pubmed	"Children" OR "Adolescent" OR "Adult" OR "Elderly" AND "Chatbot" AND "Mental Health" AND "Acceptability" OR "Effectiveness" OR "Usability" OR "Adoption" OR "Features"	16
Scopus	(TITLE-ABS-KEY ("Children" OR "Adolescent" OR "Adult" OR "Elderly") AND TITLE-ABS-KEY ("Chatbot" AND "Mental Health") AND TITLE-ABS-KEY ("Acceptability" OR "Effectiveness" OR "Usability" OR "Adoption" OR "Features"))	46
Google Scholar	allintitle: Chatbot mental health	61
Sciencedirect	("Children" OR "Adolescent" OR "Adult" OR "Elderly") AND ("Chatbot" AND "Mental Health")	51

Search sources. The literature in this scoping review study was collected from four search data sources: Pubmed, Scopus, Sciencedirect, and Google Scholar. We included all results from the years 2019 to 2023. The literature search process began on October 17 and continued until October 31, 2023.

Search terms. The keywords and terms used for the literature search were combined using the main elements, "mental health-related terms," "chatbot-related terms," "population-related terms," and "terms related to outcome measures." The search method is detailed in Table 1.

Study eligibility criteria. We included all studies or research focusing on mental health chatbots and their usage measurements. Further inclusion criteria included research populations with or without mental disorder symptoms (clinical and non-clinical), all types of chatbots (web-based, stand-alone software, and social media-based), chatbots with functions and objectives of promoting behavior, prevention, screening, and intervention, and studies conducted in English.

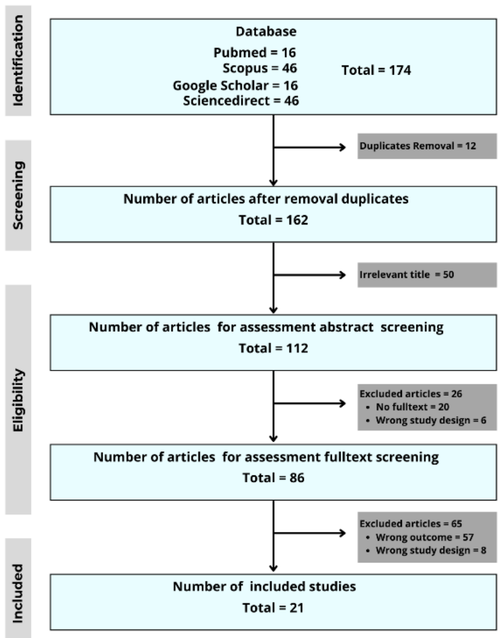

Fig 1. PRISMA Diagram

Figure 1 details the literature search process in the scoping review research. The initial literature search in the designated databases resulted in an initial screening of 172 articles. All studies were eligible for inclusion if they met the criteria listed. The inclusion criteria for this study were summarised in Table 2.

Table 2. Inclusion Criteria

Criteria	Specific Criteria
Inclusion	- User population with or without symptoms of mental health disorders.
	- Chatbots included in any form.
	- Chatbots with the purpose of behavior promotion, prevention, screening, and intervention are included.
	- Articles published from 2019 to September 2023.
	- Written in English.

2.2 Study Selection

The study and research selection process was conducted in three phases: identification, screening, and eligibility. Studies/articles were selected through the assessment of the full text that was available and relevant by two individuals. One co-author independently carried out the screening and eligibility phases.

2.3 Data Extraction and Data Synthesis

The author performed data extraction and recorded the results in table form. First, the extracted data were organized into a table, followed by synthesizing the data using a narrative approach.

3 Results and Discussion

3.1 Search Results

Four databases were used to conduct literature searches following the steps outlined in the search protocol. Subsequently, further screening based on titles narrowed it down to 112 articles. Fifty titles deemed irrelevant were then removed from the list. Further screening was then based on abstracts, resulting in 86 articles. Finally, a screening through the entire text of the articles left a total of 21 articles. The entirety of articles resulting from this screening stage will then undergo qualitative analysis and synthesis.

A total of 21 articles underwent analysis and synthesis. Approximately 43% (9/21) of the articles utilized a mixed-methods research design (quantitative and qualitative) to assess the use of mental health chatbots. There were 33% (7/21) of articles employing a Randomized Controlled Trial (RCT) design, and 14% (3/21) of articles using an experimental design without a control group (quasi-experiment). Survey and qualitative research designs each represented 5% (1/21) of the articles.

3.2 Chatbot Descriptions

Detailed characteristics of mental health chatbots are provided in Table 3.

3.2.1 Platform and chatbot name

Researchers identified that 10 out of 21 articles classified mental health chatbots as stand-alone software, which means they have their own application or space separate from other channels. Additionally, 7 out of 21 articles categorized mental health chatbots as social media based, meaning they operate through social media platforms (such as Facebook, Telegram, and WeChat). There were 4 out of 21 articles that categorized mental health chatbots as web-based, accessible via websites. All mental health chatbots included their names along with explanations.

Table 3 provides a detailed overview of the study characteristics, including study design, year of publication, sample size, sample type, setting respondents, and the platform of chatbots.

Table 3. Study Characteristics

No	Characteristics	Type	Number of Studies
1	Study Design	Quasi-experiment	3
		Survey	1
		RCT	7
		Qualitative	1
		Mix Method	9
2	Years	2019	1
		2020	1
		2021	6
		2022	6
		2023	7
3	Sample size	<50	10
		50-99	2
		100-199	3
		≥ 200	6
4	Sample type	Clinical sample	6
		Non-clinical sample	15
5	Setting	Adolescents	3
		Young people	6
		Adult	11
		Others	1
6	Platform	Stand-alone software	10
		Web-based	4
		Social media based	7

3.2.2 Sample size and sample type

Researchers identified that 10 out of 21 articles had sample sizes <50. Six articles used sample sizes ≥ 200. Meanwhile, 3 articles had sample sizes ranging from 100-199, and 2 articles used sample sizes from 50-99. The largest sample size used was 3,629, and the smallest was 6. These samples were categorized into two types: clinical samples (obtained from initial mental health diagnoses/assessments) and non-clinical samples (identified as samples without intervention or initial assessment, typically randomly obtained from a population/community). Fifteen out of 21 articles used non-clinical samples.

3.2.3 Chatbot aim (purpose)

The primary aim of chatbots was mostly a combination category (12/21), involving various services such as therapy, training, screening, self-management, counseling, and education. Replication chatbots focused specifically on online education and counseling. Xiaolv, Vickybot, and IDEABot are types of chatbots accommodating features for screening anxiety, depression, and non-specific mental health issues in users. The Chatbot 21 Day Stress Detox focused on self-management.

3.2.4 Targeted disorders

Most chatbots (13/21) focused on anxiety, depression, and stress disorders. Alex was the only chatbot targeting eating disorders (EDs), while Todaki targeted attention deficit problems (ADHD) and panic disorders.

3.2.5 Setting chatbot user

Mental health chatbots were predominantly applied in the adult category (11/21), referring to participants aged 18 years and above. Six articles used participants categorized as young people, specifically college-aged individuals. The distinction between these categories lies in the upper age cut-off, with college-aged individuals typically being up to 35 years old.

3.2.6 Measured outcome

In evaluating the feasibility and acceptance of mental health chatbots among users, parameters such as acceptability and effectiveness were primarily used. Measures of effectiveness were tailored to the targeted disorders. The Positive and Negative Affect Scale (PANAS) was frequently used to assess the performance outcomes of mental health chatbots. PANAS is a measurement tool used to identify individual emotional states across two main dimensions: positive affect (PA) and negative affect (NA). [7]

Table 4 examines the detailed studies between chatbot characteristics, focusing on measured outcome, chatbot aim, targeted disorders, and media type input-output of chatbots.

Table 4. Chatbot Characteristics

No	Characteristics	Type	Studies ID
1	Measured outcome	Acceptability	2,4,5,8,9,10,11,12,14,15,20
		Effectiveness	1,2,3,4,5,6,7,12,13,19,21
		Usability	4,5,6,17,18
		Features	3
		User Engagement	6,7,19
2	Chatbot aim	Therapy	12,17,20,21
		Training	1,2,3,4,5,6,9,10,11,12,13,17,19,21
		Screening	7,8,9,11,16
		Self-management	7,8,9,11,12,13,14,19,20,21
		Counselling	15
		Education	15,16,18,19
3	Targeted disorders	Depression	2,5,7,9,10,11,17,19,21
		Stress	1,2,6,14,17,19
		ADHD	4
		Anxiety	2,6,7,10,11,12,14,17,19,21
		Body Image	3
		Substance use disorder	9
		Panic Disorder	4
		Sleep	17
		Eating disorders	18
		Burnout	7

4	Media type input-output	Text	2,12
		Text, Emoji	3,4,10,17,18,19,20
		Text, Emoji, Image/Sound	5,6,7,9,13
		Text, Voice	8,15,16
		Teks, Image, Voice	1,13

3.3 Discussion

3.3.1 Principal findings

Most studies (11/21) aimed to evaluate mental health chatbots. This is a crucial point in developing mental health applications and evaluating user experiences to improve their effectiveness. Most studies used the Patient Health Questionnaire-9 (PHQ-9) questionnaire to gather relevant data. The PHQ-9 delivered through chatbots can be relied upon for assessing depression in adults. The psychometric properties of PHQ-9 support its integration into research using chatbots [8].

Most chatbots are standalone applications, but there is one unique chatbot integrated into a healthcare application, namely Vickybot. Vickybot is integrated into the mental health application of a hospital called PRESTOapp through collaboration with the Barcelona Supercomputing Center (BSC). Chatbots of this type are likely more familiar to users who have used the health application before [5], [9].

Mental health chatbots mostly focus on anxiety, depression, and stress. However, there is one unique chatbot that combines a focus on mental health disorders and body image, namely TOPITY. This is interesting because individuals with negative body image may suffer from depression, while those with depression may have body image issues, often making it difficult to determine which issue came first [10], [11].

There is a mental health chatbot focused on evaluating samples using employees from mental health services, namely iHelpr. There are currently no standard methods used to evaluate mental health chatbots. Most aspects are studied using user questionnaires or interviews [12], [13].

Fig 2. Chatbot Based
(Source: created by the author, 2024)

Figure 2 presents the mapping of chatbot to provides a visual representation based country-wise distribution. The data reveals a significant disparity in the global distribution of mental health chatbots, with European countries leading in chatbot development. This suggests that access to such technological interventions may be unevenly distributed on a global scale.

3.3.2 Concepts and methods for measured outcome

Mixed methods are the research design used in assessing the use of mental health chatbots. The concept of measuring chatbots predominantly uses The System Usability Scale (SUS) to explore user experience (UX/User Experience). SUS is useful for assessing the usability and functionality of various products, including chatbots [14].

The concept of measuring the Positive and Negative Affect Scale (PANAS) is most commonly used in studies to identify individuals' emotional states with two main dimensions: positive affect (PA) and negative affect (NA). High scores on the PA dimension indicate that individuals experience emotions characterized by positive valence and excited arousal [7]. Testing of mental health chatbots is predominantly conducted in non-clinical groups (15/21). This is because the general goal of strategies to address mental health is to prevent the onset of symptoms [15].

3.3.3 Strengths and limitations

The results reported are based on the Preferred Reporting Items for Systematic reviews and Meta-Analyses extension for Scoping Reviews (PRISMA-ScR) Checklist [16]. Previous reviews on mental health chatbots tend to focus on targeting anxiety and depression disorders and exploring their features. In this review, readers can further explore the use and measurement assessment of these chatbots. This review only used 4 sources, which might overlook some other relevant studies. Additionally, types of systematic review and meta-analysis studies from the search results were not included, thereby potentially missing out on relevant research regarding mental health chatbots.

Table 5. Methodology and Types of Outcome/Assessment Results in the Use of Mental Health Chatbots

No	Author	Chatbot Name	Chatbot Based	Study Design	Setting	Measured Outcome	Platform	Targeted Disorders	Media Type	Chatbot Aim
1	(Schillings et al., 2023) [17].	ELME - (Everyday-life Mindfulness Experience)	Germany	Randomised Controlled Trial	Adult >= 18 years old	Effectiveness	Web-based	Stress	Text, voice, image	Training
2	(Wrightson-Hester et al., 2023) [18].	MYLO - (Manage Your Life Online)	Western Australia	Mixed Methods (RCT and Qualitative)	Young people aged 16 to 24 years	Effectiveness, Feasibility, Acceptability	Stand-alone software	Stress, Depression, Anxiety	Text	Training
3	(Matheson et al., 2021) [19].	TOPITY - Body image Scale	Brazilian	Randomised Controlled Trial	Adolescents aged 13-18 years	Effectiveness, Features	Social media based	Body Image and Mental Health	Text, emoji	Training
4	(Jang et al., 2021) [20].	TODAKI -“patting”	Korean	Randomised Controlled Trial	Adult aged 19–60 years	Effectiveness, Usability, Acceptability	Stand-alone software	Attention deficit problems (ADHD) and Panic Disorder	Text, emoji	Training
5	(He et al., 2022) [21].	XiaoE	Chinese	Randomized Controlled Trial	College students age 17-34 years	Effectiveness, Usability, Acceptability	Stand-alone software	Depression	Text, image, and voice	Training
6	(Gabrielli et al., 2021) [22].	Atena	Italy	Mixed Methods (RCT and Qualitative)	University students in their first year	User Engagement, Effectiveness, Usability	Stand-alone software	Anxiety and Stress	Text, image, and voice	Training

No	Author	Chatbot Name	Chatbot Based	Study Design	Setting	Measured Outcome	Platform	Targeted Disorders	Media Type	Chatbot Aim
7	(Anmella et al., 2023) [23].	Vickybot	Spain	Quasi-experiment	Health Worker and General Praticer aged between 18 and 65 years	Feasibility, Effectiveness, User-Engagement	Stand-alone software (PRESTO)	Anxiety, Depressive symptoms and Burnout	Text, image, and voice	Screening, Self-management
8	(Viduani et al., 2023) [24].	IDEABot	Brazilian	Mixed Methods (Survey and Qualitative)	Adolescents aged 14 to 16 years	Acceptability	Web-based	Depression	Text, voice,	Screening, Self-management
9	(Prochaska et al., 2021) [25].	Woebot-SUDs	American	Quasi-experiment	American adults (aged 18-65 years)	Feasibility, Acceptability, and Preliminary Efficacy	Stand-alone software	Substance use disorder	Text, image, and voice	Screening, Self-management, Training
10	(Bendig et al., 2021) [26].	SISU	Germany	Mixed Methods (Quasi-experiment and Qualitative)	University students 18 years of age or older	Feasibility, Acceptability	Stand-alone software	Mood, Depression, Anxiety	Text, emoji	Training
11	(Chiauzzi et al., 2023) [27].	W-GenZD	American	Randomized Controlled Trial	Youths aged 13-17 years	Feasibility and Acceptance	Stand-alone software	Depression and/or Anxiety	Text, image, and voice	Screening, Self-management, Training
12	(Goonesekera & Donkin, 2022) [28].	Otis	New Zealand	Mixed Methods	Participants aged 18 years and older	Feasibility, Acceptability, Engagement, and Effectiveness	Social media based	Anxiety	Text	Therapy, Training, Self-management

No	Author	Chatbot Name	Chatbot Based	Study Design	Setting	Measured Outcome	Platform	Targeted Disorders	Media Type	Chatbot Aim
13	(Potts et al., 2023) [29].	ChatPal	Northern Ireland, Scotland, the Republic of Ireland, Sweden, and Finland.	Mixed Methods	Adult aged between 18 and 73 (mean 30) years	Effectiveness, Feasibility	Stand-alone software	Mental Health and Well-Being	Text, emoji, image	Training, Self-manage ment
14	(Williams et al., 2021) [30].	21 Day Stress Detox	New Zealand	Mixed Methods	University students 18–24 years of age	Feasibility and Acceptability	Social media based	Well-being, Stress, and Anxiety	Text, image	Self-manage ment
15	(Skjuve et al., 2021) [31].	Replika	Europe, the Americas and Asia	Qualitative	Adult ranging from 17–62 years	Sentiments Towards Replika, Acceptability	Social media based	Mental Health and Well-Being	Text, voice	Counselling and Education
16	(Zhu et al., 2022) [32].	Xiaolv	China (Wuhan dan Chongqing)	Quantitative Survey	Adult ranging from 18–60 years	User experience and User satisfaction	Social media based	Mental Health Disorders	Text, voice	Screening, Education
17	(Cameron et al., 2019) [33].	iHelpr	UK (United Kingdom)	Mixed Methods	Employees from a mental health social enterprise (25-34 years)	Usability	Web-based	Stress, Anxiety, Depression, Sleep, and Self Esteem	Text, Emoji	Training, Therapy, Self-manage ment
18	(Shah et al., 2022) [34].	Alex	Stanford-Wa shington	Mixed Methods	Adult at least 18 years old	Usability	Social media based	Eating Disorders (EDs)	Text, Emoji	Education

No	Author	Chatbot Name	Chatbot Based	Study Design	Setting	Measured Outcome	Platform	Targeted Disorders	Media Type	Chatbot Aim
19	(Daley et al., 2020) [35].	ViTalk	Brazil	Quasi-experiment	Adult over 18 years of age	Engagement and Effectiveness	Stand-alone software	Anxiety, Depression and Stress	Text, Emoji	Training, Self-management, Education
20	(Sabour et al., 2023) [36].	Emohaa	China	Randomised Controlled Trial	Adult over 18 years of age	Acceptability and Feasibility	Social media based	Mental Distress	Text, Emoji	Therapy, Training, Self-management
21	(Romanovskyi et al., 2021) [37].	Elomia	Ukraine	Randomised Controlled Trial	University student ages 19 to 23 years old	Effectiveness	Web-based	Anxiety, Depression and Emotional States.	Text, Emoji	Training, Self-management

4 Conclusion

Chatbots are still a very new application in the field of mental health. The main purposes of using chatbots are typically a combination of education, training, and self-management. The target users are generally adults who are deemed capable of utilizing the application. The combination of focusing on mental health disorders and integrating chatbot applications with healthcare services is a crucial point in their development process. Chatbots offer a non-judgmental alternative. Users feel more comfortable using the technology anonymously compared to face-to-face communication with professionals. Chatbots can also be used to identify general symptoms of mental health disorders. However, this initial detection is not intended to replace a clinical diagnosis by professional healthcare providers.

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