# A Review of Knowledge-Based Interventions for Mental Health Self-Management

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**ABSTRACT----** ***Mental health disorders have affected people's everyday lives globally, showing rapid growth. Effective detection, diagnosis, and treatment of MSDs can occur by utilizing increasingly large amounts of available health data from different sources. However, there are many challenges in developing effective treatment models for this condition. The challenges are further complicated by the volume, heterogeneity, interoperability, propagation, and complexity of data, especially with the emergence of big data. Knowledge management and knowledge-based systems have significantly impacted healthcare quality and delivery, especially patient self-management. In this work, we review knowledge-based applications for mental health self-management. The research efforts are synthesized, discussing shortcomings and future research directions.***

**Keywords---** Conversational agents, knowledge base, mental health, semantic networks

## 1. 1. INTRODUCTION

Mental health illnesses have affected people's everyday lives globally, showing rapid growth. The burden of mental illnesses continues growing, with significant impacts on health and primary social, human rights, and economic consequences worldwide. There are many variations and types of mental illnesses – depression, bipolar disorder, dementia, schizophrenia, characterized by a combination of abnormal thoughts, perceptions, emotions, and behavior [1]. Access to health care and social services capable of providing treatment and social support is vital. Approximately one in five adults in the United States (U.S.) struggle with mental illness [2]; however, many individuals are not receiving treatment. Worldwide estimates show that 70% of people with mental illness receive no formal treatment globally [3], [4]. Over a quarter of individuals with elevated levels of depression and anxiety and 12.8% of the U.S. population reported an unmet need for mental health counseling or therapy [5]. Low perceived need for treatment (believing the problem is not severe), preference to handle the situation alone, and attitudinal barriers like perceived stigma define lack of access to care. Other factors, such as lack of belief in treatment efficacy, increased demand for mental health services (especially psychotherapy and counseling) with a shortage of mental health professionals, particularly in rural and low-income areas, are responsible for the barriers/issues with access to care [6]–[8]. With the unmet needs of mental health services and a stretch in available resources and services, patient self-management is beginning to emerge as an option to ensure availability of care and support.

Self-management is defined as "participating in education or treatment designed to bring about specific outcomes, preparing people to manage their health condition on a day-to-day basis, practicing specific behaviors, and having the skills and abilities to reduce the physical and emotional impact of the illness with or without the collaboration of the healthcare team" [9]. The World Health Organization (WHO) describes self-management as "putting patients or service users in direct control of managing their conditions by enabling them to cope in one or more of the following areas: problem-solving, goal setting, identifying triggers, and indicators of deteriorating health; and responding to these themselves before relying on clinician-led intervention" [10]. Self-management is also an individual's ability to manage symptoms, treatments, physical and psychosocial consequences, and lifestyle changes [11] independently and integrate them into daily life. Self-management can enable individuals to learn more about and participate actively in their care process. The prevalence of barriers to access to care and the potential of self-management have prompted technological advancements to meet these needs.

### 1.1. AI-Based Interventions for Healthcare

The increasing evolution of technologies has resulted in cutting-edge advances in recent years, with artificial intelligence (AI) leading the pack [12], [13]. Health care institutions are fast becoming connected knowledge-based communities of practice for sharing knowledge, reducing administrative costs, and improving the quality of care [14]. AI can potentially transform patient healthcare with its extensive power. AI techniques provide effective knowledge management, sharing, decision-making, and support [15]. It supports healthcare practitioners in patient care by providing up-to-date health information synthesized from publications and clinical practices. It also enables knowledge sharing amongst clinicians to make accurate decisions via knowledge-based systems [13]. Knowledge-based systems (KBSs) are AI-based systems that use information from various sources to generate new decision-making and problem-solving knowledge. These systems have built-in problem-solving capabilities and rely extensively on data to provide accurate results. KBSs comprise a repository of expert knowledge (knowledge base) and an inference engine with retrieval features to allow expertise or knowledge sharing. It supports human decision-making using knowledge-based techniques. KBS is a vital application of AI in current settings, especially in the healthcare domain. They give expert-level, problem-specific advice and assist in decision-making in medical data interpretation, patient monitoring, disease diagnosis, treatment selection, prognosis, and patient management [16]. Some possible examples include:

- Mobile apps with AI-driven chatbots that offer personalized coping strategies and support based on the individual's emotional state and needs.
- Web-based platforms that use AI algorithms to analyze user data and provide personalized mental health recommendations and resources.
- Virtual reality environments designed to simulate exposure therapy for specific phobias or anxiety disorders.
- Online communities and forums that leverage AI to provide support, education, and resources to individuals with mental health conditions.

Technology-based interventions for management (including self-management) and support in healthcare are increasing in adoption rate, offering a potential solution to overcome barriers to treatment because they are easily accessible and cost-effective [17]. It further reduces wait times and provides anonymity and flexibility in terms of time and location of use. IT solutions can promote fundamental principles of self-management, namely education, empowerment, and collaboration. Positive clinical outcomes have been demonstrated for several chronic conditions when IT solutions were incorporated into self-management programs [9]. These interventions are ubiquitous, with increasingly powerful technical abilities, wide acceptability in several domains, and growing evidence in mental health care services. According to the World Health Organization, more than one-fourth of 15,000 mobile health (mHealth) apps focus on mental health diagnosis or support [7], [18].

This systematic literature review reviews knowledge-based interventions' characteristics, architectures, and applications specifically for mental health self-management. We summarize and synthesize findings from existing studies. The review seeks to answer the following questions as they relate to mental health:

- What types of knowledge-based self-management interventions have been developed?
- What is the current evidence on knowledge-based systems in psychiatry, specifically mental healthcare?

## 2. METHODS

We searched PubMed, Embase, CINAHL, PsycInfo, and ACM Digital Library using a predefined search strategy. The studies were included if they: (1) were primary research studies focused on knowledge-based digital interventions for mental health self-management; (2) were published in the past six years to understand current applications. In addition, backward and forward reference list checking of the included studies and relevant reviews was conducted. A narrative data synthesis was performed to elaborate on the development and applications of KBS for mental health and summarise areas for future research.

## 3. RESULTS

We discuss our findings under the following themes: KBS approaches and tools (based on inference engine) and KBS applications.

### 3.1 KBS tools for decision support

A KBS tool is a set of software instructions and utilities taken to be a software package designed to assist the development of knowledge-based systems. Some of the standard tools identified from the review include:

*Case-based reasoning (CBR):* Among the numerous AI concepts, case-based reasoning (CBR) has attracted much attention. CBR is a problem-solving approach that relies on past and similar cases to solve new problems. It simulates human decision-making processes and enables the accumulation of previous experience. Case-based reasoning means retrieving former, already solved problems like the current one and modifying their solutions to fit the current problem. One of the essential advantages of CBR is its learning capability. Its problem-solving ability improves with the increasing number of accumulated cases. Nevertheless, in contrast, its problem-solving ability is poor when few cases are in the case base.

*Rule-based reasoning (RBR):* RBR is a natural knowledge representation of IF-THEN rule statements. Rules are simply patterns and an inference engine searches for patterns in the rules that match patterns in the data. For RBR, the problem-solving ability is sustained throughout the whole process. However, its learning capability is poor because rules involving new expertise are difficult to acquire. The rules applied to solve the problem can be traced with the rule-based reasoning technique, which is helpful because the logic behind the solution can easily be understood.

*Fuzzy theory:* Fuzzy theory is a theory of classes with unclear boundaries. Fuzzy logic provides methods to represent and reason with ambiguous terms. Fuzzy logic focuses on diagnosing the criteria and the severity of a particular episode or disorder. A set of questions will be given based on the specific condition being diagnosed, and certain points are assigned to each possible answer for each question.

*Fuzzy-genetic Algorithm:* Fuzzy-genetic algorithm (fuzzy-GA) is used to determine and propose the suitable treatment for each person with a mental health condition based on their budget and overall health conditions. This gives each patient several options on choosing a treatment plan that fits the patient's budget without jeopardizing the patient's prevailing health conditions.

### 3.2 KBS Technologies and Applications

**Agent-based systems/ Conversational agents:** Also known as Chatbots, they are automated computer programs that can hold, e.g., a script-based conversation with a human being [19]. These systems can converse and interact with human users using natural language, either written or voice, and visual language. Conversational agents can potentially communicate with patients and serve as practical self-management tools for chronic conditions, including mental disorders [20]. Chatbots can either be rule-based or intelligent chatbots. Rule-based chatbots work with predefined rules or decision trees to manage their response and dialog, while intelligent chatbots use artificial intelligence (AI) to generate dialogue. Chatbots have become popular in health care, specifically mental health, in the past five years. According to a review of chatbot use in mental healthcare generally [7], [21] and clinical psychology and psychotherapy (precisely) [19], different chatbots were identified for purposes such as therapy, training, education, counseling, and screening. They also effectively improved mental health disorders such as depression, stress, and acrophobia. Some of the prominent chatbots in literature are discussed briefly below.

ELIZA – the first attempt at building a mental health chatbot by Joseph Weizenbaum in 1966. Using natural language processing rules, it generates appropriate textual responses to users' typed inputs through questions and answers. Despite its technical simplicity, ELIZA can generate convincing dialogues and evidence of therapeutic effectiveness [19], [22]. However, there has been no significant attempt at fully automating its approach for treating mental health problems. The MYLO chatbot, powered by a method-of-level therapy script, offers a self-help program for problem-solving when a person is in distress [22]. The chatbot imparts problem-solving strategies and guides users to focus on a specific problem by using open questions to encourage them to reflect on their thoughts, feelings, and behaviour. When evaluated, participants rated MYLO as practical and helpful in reducing problem-related distress compared to ELIZA. WOEBOT, a CBT-based chatbot, encourages learning by offering a self-help program to reduce anxiety and depression [23]. Users reported significant overall satisfaction with usage and content of the chatbot when evaluated.

SHIM [24] and SABORI [25] are also CBT-based chatbots offering self-help programs for promoting mental well-being [24]. During a randomized control trial, SHIM effectively increased psychological well-being and reduced stress in a non-clinical population. On the other hand, SABORI seeks to increase patient engagement and adherence via a preventive approach. The chatbot uses behavior intention questions to respond to user inputs and suggest a behavior. However, it is limited in its functions as it is domain-specific. Other chatbots include GABBY (based on the mindfulness principles), which offers self-help programs for behavioral changes and stress management [26]; PEACH chatbot for intentional personality change through non-clinical psychological coaching [27]; Vivibot, an evidence-based conversational agent to address psychosocial needs of young people treated for cancer [28]. SERMO for emotions regulation [29], [30]; Tess, an AI-based chatbot that delivers brief text conversations as comprehensive support for mental health [31], [32]; iHelpr [33]; Anna [6]; Wysa and Joy [34] are also instances of chatbot studies in the literature.

**Semantic Web/Network:** Semantic web and technologies provide a new approach to managing information and processes by creating and using semantic metadata – which can describe the document or entities within the document. Semantic web-based knowledge bases include:

*Knowledge Graphs (KGs):* Knowledge Graphs are current AI trends that are particularly effective to model and perform automated domain-specific reasoning tasks [35]. A knowledge graph (KG) is an interconnected dataset enriched with semantics to reason about the underlying data and use it confidently for complex decision-making [36]. Knowledge Graphs (KGs) create structured information about entities and their relations from information retrieved from several resources (different silos). They are represented by a predefined ontology that uses different classes and the relationships identified using a semantic network [37], [38]. Knowledge graphs provide deep, dynamic context – and simplify complex concepts, thereby providing related information in one place, with all the relationships across that data. Generic KGs include Google KG [39], scientific, e.g., Semantic Scholar and PID [40], DBpedia, and YAGO [37]. KGs have formed the bedrock of many knowledge-based applications in healthcare, ranging from extracting patient records and diagnoses to data integration on drugs and interactions [41]–[43]. KGs can organize and deliver quality mental health information to the public. However, preliminary evidence suggests the sparseness of mental health KGs [44]. Existing attempts at KGs for mental health include implementing the DepressionKG system [41] to explore the relationships among various knowledge resources about depression for clinical decision support; MDepressionKG, a model of knowledge graph linking all metabolism entities of humans and their microbes to depression disorder [45]. A mental health question and answering system (MHQ&A) was proposed by Guo et al. [46]. Drawing on knowledge graph technology, the system provides the public answers to primary mental health questions, especially depression. Also, using social media data (Twitter), a semantic graph was developed to represent correlations between depression and its symptoms. Cao et al. [47] developed a high-level suicide-oriented personal knowledge graph with deep neural networks for suicidal ideation detection on social media.

*Ontologies:* An ontology is a standardized computational artifact that captures, represents, and reasons about the knowledge in the field [48]. Ontologies capture knowledge by defining concepts, instances, relationships, and axioms while increasing the interoperability between different data sources and systems. They also reveal new associations between the datasets with corresponding semantics, inferring new knowledge. Ontologies are widely used in health and biomedicine and have substantially contributed to translational and clinical research and public and personalized health care. A formal ontology was implemented by Brenas et al. [48] to understand the relationship between adverse childhood experiences (ACEs), corresponding risk factors, and associated health outcomes. The ontology promises to improve ACEs research by allowing data integration and knowledge modeling. We also find a mental health ontology implemented by Hadzic et al. [49], which provides information on disorder types, factors (causality), and treatment. To accurately infer the probability of depression, a depression-terminology ontology incorporated with Bayesian networks was implemented in Chang et al. [50], while further reviews also identify the existence of Ontologies for other mental conditions like Alzheimer's [51] and Parkinson's [52].

**Expert Systems:** Expert systems (generally knowledge-based) solve problems using domain-specific knowledge. Expert systems are complex AI systems that utilize experts' learning in a specific problem domain to support decision-making [53]. The knowledge base (KB) is the core of the ES. Expert systems' knowledge bases can be rules or AI-based, allowing their implementation to different domains. The application of ES to healthcare dates back several decades. Recent applications to mental health care include designing a procedural rule-based expert system (RBES) using an interactive question-and-answer sequence to diagnose psychiatric diseases [54].

## 4. DISCUSSION

We reviewed KBS for mental health and identified emerging application areas. More recent research on self-management and care has involved conversational agents for mental health and semantic-based KBS. Conversational agents (chatbots) can be practical, engaging, and valuable tools for individuals with mental disorders, ensuring privacy and preventing stigmatization. The chatbot technology is still experimental, as most reported chatbots are pilots undergoing controlled trials. Although the benefits of using chatbots for mental healthcare are numerous, there are still concerns among users and relevant stakeholders. Preliminary evidence validates the potential of chatbots, but high-quality evidence is required from more extensive and diverse samples, including clinical populations. It is also essential to compare these interventions to traditional treatments to ascertain the magnitude, efficacy, feasibility, sustainability, safety, and acceptance of chatbots. Another interesting scope of research is designing chatbots that can detect emotions from users and offer corresponding emotional support.

As with all knowledge bases (KBs), there is high heterogeneity in the implementation methodologies of conversational agents. There are no typical implementation, testing, evaluation, or reporting standards. Further research can investigate ways to evolve practical chatbot implementation approaches to foster transferability and replication in other contexts. To ascertain the validity and authenticity of the contents of chatbots and design more personalized content, it is essential to involve all mental health stakeholders in the development process. Ensuring substantial involvement will further inform the design of personalized, targeted, and evidence-based chatbots. Finally, it is also vital to understand preferred engagement modes for optimal usage, identify methods of embedding these agents into medical systems and applications, and adapt them to suit local content.

Semantic-based KBs are a modern way to store information with different KGs built for domains. Some typical application trends of KGs include integrating and leveraging data from diverse sources at a large scale and combining deductive (rules, ontologies) and inductive techniques (machine learning, analytics) to represent and accumulate knowledge. KG helps to achieve interoperability, interlinking, and integration. However, the dynamic nature of knowledge will pose a limitation. Instances of various classes may be added or deleted, and the semantic relationship between elements might also evolve. When such changes occur, a knowledge graph might become inconsistent with its ontology, conveying meaningless information. Future research can investigate designing quality, scalable, and dynamic KGs. With expert systems, current research focuses on evolving technical evaluation standards and domain-specific customization of knowledge bases for ES.

Knowledge-based systems offer several advantages - knowledge is captured and represented efficiently and securely, synthesized, and integrated from different knowledge sources to proffer solutions to complex problems. KBS creates new knowledge by inductive reasoning and makes such a learning process transferable. Generally, most KBSs are rule-based and are therefore prone to anomalies [55] such as redundancy (the presence of rules drawing the same inferences with the same input), conflict (a situation where incompatible inferences are made from valid initial data), circularity (when a set of rules run endlessly during an inference process) and deficiency. It is, therefore, essential to check for anomalies when building a knowledge-based system. In addition, dynamic events like domain changes, evolving user requirements, and KBS customization may warrant modifications to the knowledge base, which is a complex process. Future research could investigate developing techniques for knowledge base modification.

## 5. CONCLUSION

The potential benefits of KBSs and their technologies have made it an exciting method of delivering health care support, especially in mental health. With their ability to create and provide access to new knowledge to support decision-making, knowledge bases would make it possible for healthcare institutions to enhance the quality of patient care and access to care while promoting self-management, especially for mental health. This review outlines some of the benefits, applications, limitations, and possible challenges posed by the emerging applications of knowledge-based systems.

## 6. REFERENCES

[1] S. L. James *et al.*, "Global, regional, and national incidence, prevalence, and years lived with disability for 354 Diseases and Injuries for 195 countries and territories, 1990-2017: A systematic analysis for the Global Burden of Disease Study 2017," *Lancet*, vol. 392, no. 10159, pp. 1789–1858, Nov. 2018, DOI: 10.1016/S0140-6736(18)32279-7.

[2] K. R. Merikangas *et al.*, "Lifetime prevalence of mental disorders in U.S. adolescents: Results from the national comorbidity survey replication-adolescent supplement (NCS-A)," *J. Am. Acad. Child Adolesc. Psychiatry*, vol. 49, no. 10, pp. 980–989, Oct. 2010, DOI: 10.1016/j.jaac.2010.05.017.

[3] P. S. Wang, M. Lane, M. Olfson, H. A. Pincus, K. B. Wells, and R. C. Kessler, "Twelve-Month Use of Mental Health Services in the United States: Results From the National Comorbidity Survey Replication," *Arch. Gen. Psychiatry*, vol. 62, no. 6, pp. 629–640, Jun. 2005, doi: 10.1001/ARCHPSYC.62.6.629.

[4] P. S. Wang *et al.*, "Use of mental health services for anxiety, mood, and substance disorders in 17 countries in the WHO world mental health surveys," *Lancet*, vol. 370, no. 9590, pp. 841–850, Sep. 2007, doi: 10.1016/S0140-6736(07)61414-7.

[5] J. M. Nagata *et al.*, "Prevalence and Sociodemographic Correlates of Unmet Need for Mental Health Counseling Among Adults During the COVID-19 Pandemic," *https://doi.org/10.1176/appi.ps.202100111*, p. appi.ps.2021001, Jun. 2021, doi: 10.1176/APPI.PS.202100111.

[6] E. M. Boucher *et al.*, "Artificially intelligent chatbots in digital mental health interventions: a review," *https://doi.org/10.1080/17434440.2021.2013200*, vol. 18, no. sup1, pp. 37–49, Dec. 2021, DOI: 10.1080/17434440.2021.2013200.

[7] A. A. Abd-alrazaq, M. Alajlani, A. A. Alalwan, B. M. Bewick, P. Gardner, and M. Househ, "An overview of the features of chatbots in mental health: A scoping review," *Int. J. Med. Inform.*, vol. 132, p. 103978, Dec. 2019, doi: 10.1016/J.IJMEDINF.2019.103978.

[8] B. A. J. Van Spijker, M. Cristina Majo, F. Smit, A. Van Straten, and A. J. F. M. Kerkhof, "Reducing Suicidal Ideation: Cost-Effectiveness Analysis of a Randomized Controlled Trial of Unguided Web-Based Self-help," *J Med Internet Res 2012;14(5)e141 https//www.jmir.org/2012/5/e141*, vol. 14, no. 5, p. e1966, Oct. 2012, DOI: 10.2196/JMIR.1966.

[9] S. W. Ong, S. V. Jassal, E. Porter, A. G. Logan, and J. A. Miller, "Using an Electronic Self-Management Tool to Support Patients with Chronic Kidney Disease (CKD): A CKD Clinic Self-Care Model," *Semin. Dial.*, vol. 26, no. 2, pp. 195–202, Mar. 2013, doi: 10.1111/SDI.12054.

[10] D. Crepaz-Keay, "Self-management of mental health problems," 2010.

[11] A. C. Griffin *et al.*, "Conversational Agents for Chronic Disease Self-Management: A Systematic Review," *AMIA Annu. Symp. Proc.*, vol. 2020, p. 504, 2020.

[12] J. Balakrishnan, Y. K. Dwivedi, L. Hughes, and F. Boy, "Enablers and Inhibitors of AI-Powered Voice

Assistants: A Dual-Factor Approach by Integrating the Status Quo Bias and Technology Acceptance Model," *Inf. Syst. Front. 2021*, vol. 1, pp. 1–22, Oct. 2021, doi: 10.1007/S10796-021-10203-Y.

[13] O. A. Nasseef, A. M. Baabdullah, A. A. Alalwan, B. Lal, and Y. K. Dwivedi, "Artificial intelligence-based public healthcare systems: G2G knowledge-based exchange to enhance the decision-making process," *Gov. Inf. Q.*, p. 101618, Aug. 2021, doi: 10.1016/J.GIQ.2021.101618.

[14] R. Bose, "Knowledge management-enabled health care management systems: capabilities, infrastructure, and decision-support," *Expert Syst. Appl.*, vol. 24, no. 1, pp. 59–71, Jan. 2003, DOI: 10.1016/S0957-4174(02)00083-0.

[15] Y. K. Dwivedi *et al.*, "Artificial Intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy," *Int. J. Inf. Manage.*, vol. 57, p. 101994, Apr. 2021, doi: 10.1016/J.IJINFOMGT.2019.08.002.

[16] K. P. Adlassnig, "The Section on Medical Expert and Knowledge-Based Systems at the Department of Medical Computer Sciences of the University of Vienna Medical School," *Artif. Intell. Med.*, vol. 21, no. 1–3, pp. 139–146, Jan. 2001, DOI: 10.1016/S0933-3657(00)00078-6.

[17] S. Hauser-Ulrich, H. Künzli, D. Meier-Peterhans, and T. Kowatsch, "A smartphone-based health care chatbot to promote self-management of chronic pain (SELMA): Pilot randomized controlled trial," *JMIR mHealth uHealth*, vol. 8, no. 4, Apr. 2020, doi: 10.2196/15806/READER.

[18] A. A. Abd-Alrazaq, A. Rababeh, M. Alajlani, B. M. Bewick, and M. Househ, "Effectiveness and Safety of Using Chatbots to Improve Mental Health: Systematic Review and Meta-Analysis," *J. Med. Internet Res.*, vol. 22, no. 7, Jul. 2020, doi: 10.2196/16021.

[19] E. Bendig, B. Erb, L. Schulze-Thuesing, and H. Baumeister, "The Next Generation: Chatbots in Clinical Psychology and Psychotherapy to Foster Mental Health – A Scoping Review," *Verhaltenstherapie*, pp. 1–13, 2019, doi: 10.1159/000501812.

[20] A. C. Griffin *et al.*, "Information needs and perceptions of chatbots for hypertension medication self-management: a mixed methods study," *JAMIA Open*, vol. 4, no. 2, pp. 1–10, Apr. 2021, doi: 10.1093/JAMIAOPEN/OOAB021.

[21] A. A. Abd-Alrazaq, M. Alajlani, N. Ali, K. Denecke, B. M. Bewick, and M. Househ, "Perceptions and Opinions of Patients About Mental Health Chatbots: Scoping Review," *J Med Internet Res 2021;23(1)e17828 https//www.jmir.org/2021/1/e17828*, vol. 23, no. 1, p. e17828, Jan. 2021, DOI: 10.2196/17828.

[22] M. R. Bennion, G. E. Hardy, R. K. Moore, S. Kellett, and A. Millings, "Usability, Acceptability, and Effectiveness of Web-Based Conversational Agents to Facilitate Problem Solving in Older Adults: Controlled Study," *J Med Internet Res 2020;22(5)e16794 https//www.jmir.org/2020/5/e16794*, vol. 22, no. 5, p. e16794, May 2020, DOI: 10.2196/16794.

[23] K. K. Fitzpatrick, A. Darcy, and M. Vierhile, "Delivering Cognitive Behavior Therapy to Young Adults With Symptoms of Depression and Anxiety Using a Fully Automated Conversational Agent (Woebot): A Randomized Controlled Trial," *JMIR Ment Heal. 2017;4(2)e19 https//mental.jmir.org/2017/2/e19*, vol. 4, no. 2, p. e7785, Jun. 2017, doi: 10.2196/MENTAL.7785.

[24] K. H. Ly, A. M. Ly, and G. Andersson, "A fully automated conversational agent for promoting mental well-being: A pilot RCT using mixed methods," *Internet Interv.*, vol. 10, pp. 39–46, Dec. 2017, DOI: 10.1016/J.INVENT.2017.10.002.

[25] S. Suganuma, D. Sakamoto, and H. Shimoyama, "An Embodied Conversational Agent for Unguided Internet-Based Cognitive Behavior Therapy in Preventative Mental Health: Feasibility and Acceptability Pilot Trial," *JMIR Ment Heal. 2018;5(3)e10454 https//mental.jmir.org/2018/3/e10454*, vol. 5, no. 3, p. e10454, Jul. 2018, doi: 10.2196/10454.

[26] P. Gardiner *et al.*, "Design of the integrative medical group visits randomized control trial for underserved patients with chronic pain and depression," *Contemp. Clin. Trials*, vol. 54, pp. 25–35, Mar. 2017, doi: 10.1016/J.CCT.2016.12.013.

[27] M. Stieger, M. Nißen, D. Rüegger, T. Kowatsch, C. Flückiger, and M. Allemand, "PEACH, a smartphone- and conversational agent-based coaching intervention for intentional personality change: Study protocol of a randomized, wait-list controlled trial," *BMC Psychol.*, vol. 6, no. 1, pp. 1–15, Sep. 2018, doi: 10.1186/S40359-018-0257-9/FIGURES/3.

[28] S. Greer, D. Ramo, Y. J. Chang, M. Fu, J. Moskowitz, and J. Haritatos, "Use of the Chatbot 'Vivibot' to Deliver Positive Psychology Skills and Promote Well-Being Among Young People After Cancer Treatment: Randomized Controlled Feasibility Trial," *JMIR Mhealth Uhealth 2019;7(10)e15018 https//mhealth.jmir.org/2019/10/e15018*, vol. 7, no. 10, p. e15018, Oct. 2019, DOI: 10.2196/15018.

[29] M. Kraus, P. Seldschopf, and W. Minker, "Towards the Development of a Trustworthy Chatbot for Mental Health Applications," *Lect. Notes Comput. Sci. (including Subser. Lect. Notes Artif. Intell. Lect. Notes Bioinformatics)*, vol. 12573 LNCS, pp. 354–366, Jun. 2021, doi: 10.1007/978-3-030-67835-7_30.

[30] K. Denecke, A. Abd-Alrazaq, and M. Househ, "Artificial Intelligence for Chatbots in Mental Health: Opportunities and Challenges," *Lect. Notes Bioeng.*, pp. 115–128, 2021, DOI: 10.1007/978-3-030-67303-1_10.

[31] M. C. Klos, M. Escoredo, A. Joerin, V. N. Lemos, M. Rauws, and E. L. Bunge, "Artificial Intelligence–Based Chatbot for Anxiety and Depression in University Students: Pilot Randomized Controlled Trial," *JMIR Form Res 2021;5(8)e20678 https//formative.jmir.org/2021/8/e20678*, vol. 5, no. 8, p. e20678, Aug. 2021, DOI: 10.2196/20678.

[32] G. Dosovitsky, B. S. Pineda, N. C. Jacobson, C. Chang, M. Escoredo, and E. L. Bunge, "Artificial Intelligence Chatbot for Depression: Descriptive Study of Usage," *JMIR Form Res 2020;4(11)e17065 https//formative.jmir.org/2020/11/e17065*, vol. 4, no. 11, p. e17065, Nov. 2020, DOI: 10.2196/17065.

[33] G. Cameron *et al.*, "Best Practices for Designing Chatbots in Mental Healthcare – A Case Study on iHelpr," Jul. 2018, doi: 10.14236/EWIC/HCI2018.129.

[34] K. Kretzschmar, H. Tyroll, G. Pavarini, A. Manzini, I. Singh, and NeurOx Young People's Advisory Group, "Can Your Phone Be Your Therapist? Young People's Ethical Perspectives on the Use of Fully Automated Conversational Agents (Chatbots) in Mental Health Support.," *Biomed. Inform. Insights*, vol. 11, p. 1178222619829083, Mar. 2019, doi: 10.1177/1178222619829083.

[35] L. Bellomarini *et al.*, "COVID-19 and Company Knowledge Graphs: Assessing Golden Powers and Economic Impact of Selective Lockdown via AI Reasoning *," 2020.

[36] Neo4j Inc., “Neo4j – The #1 Platform for Connected Data.” 2018.

[37] D. E. O'Leary, "Enterprise knowledge graphs with applications to continuous monitoring systems," *Intell. Syst. Accounting, Financ. Manag.*, vol. 28, no. 1, pp. 84–93, Jan. 2021, doi: 10.1002/isaf.1491.

[38] T. Yu *et al.*, "Knowledge graph for TCM health preservation: Design, construction, and applications," *Artif. Intell. Med.*, vol. 77, pp. 48–52, Mar. 2017, doi: 10.1016/J.ARTMED.2017.04.001.

[39] T. K. Singhal, "Impact of social media expressions on engagement and trust of customers," *Amity Bus. Sch.*, 2015.

[40] P. Manghi, A. Mannocci, F. Osborne, D. Sacharidis, A. Salatino, and T. Vergoulis, "New Trends in Scientific Knowledge Graphs and Research Impact Assessment," 2021, DOI: 10.1162/qss_e_00160.

[41] X. He, H. Zhang, and J. Bian, "User-centered design of a web-based crowdsourcing-integrated semantic text annotation tool for building a mental health knowledge base," *J. Biomed. Inform.*, vol. 110, p. 103571, Oct. 2020, doi: 10.1016/J.JBI.2020.103571.

[42] Y. Fang, H. Wang, L. Wang, R. Di, and Y. Song, "Diagnosis of COPD Based on a Knowledge Graph and Integrated Model," *IEEE Access*, vol. 7, pp. 46004–46013, 2019, DOI: 10.1109/ACCESS.2019.2909069.

[43] X. Tao *et al.*, "Mining Health Knowledge Graph for Health Risk Prediction The paper makes significant contributions to the advancement of knowledge in data mining with an innovative classification model specifically crafted for domain-based data. In addition, by accessing the."

[44] Z. Huang, J. Yang, F. van Harmelen, and Q. Hu, "Constructing Knowledge Graphs of Depression," *Lect. Notes Comput. Sci. (including Subser. Lect. Notes Artif. Intell. Lect. Notes Bioinformatics)*, vol. 10594 LNCS, pp. 149–161, 2017, doi: 10.1007/978-3-319-69182-4_16.

[45] C. Fu, X. Jiang, T. He, and X. Jiang, "MDepressionKG: A knowledge graph for metabolism-depression associations," *ACM Int. Conf. Proceeding Ser.*, pp. 63–68, Oct. 2021, DOI: 10.1145/3500931.3500944.

[46] C. Guo, S. Lin, Z. Huang, and Y. Yao, "Mental Health Question and Answering System Based on Bert Model and Knowledge Graph Technology," *Proc. 2nd Int. Symp. Artif. Intell. Med. Sci.*, 2021, doi: 10.1145/3500931.

[47] L. Cao, H. Zhang, and L. Feng, "Building and Using Personal Knowledge Graph to Improve Suicidal Ideation Detection on Social Media," *IEEE Trans. Multimed.*, 2020, DOI: 10.1109/TMM.2020.3046867.

[48] J. H. Brenas, E. K. Shin, and A. Shaban-Nejad, "Adverse Childhood Experiences Ontology for Mental Health Surveillance, Research, and Evaluation: Advanced Knowledge Representation and Semantic Web Techniques," *JMIR Ment Heal. 2019;6(5)e13498 https//mental.jmir.org/2019/5/e13498*, vol. 6, no. 5, p. e13498, May 2019, DOI: 10.2196/13498.

[49] M. Hadzic, M. Chen, and T. S. Dillon, "Towards the mental health ontology," *Proc. - IEEE Int. Conf. Bioinforma. Biomed. BIBM 2008*, pp. 284–288, 2008, DOI: 10.1109/BIBM.2008.59.

[50] Y. S. Chang, W. C. Hung, and T. Y. Juang, "Depression diagnosis based on ontologies and bayesian networks," *Proc. - 2013 IEEE Int. Conf. Syst. Man, Cybern. SMC 2013*, pp. 3452–3457, 2013, DOI: 10.1109/SMC.2013.589.

[51] A. Malhotra, E. Younesi, M. Gündel, B. Müller, M. T. Heneka, and M. Hofmann-Apitius, "ADO: A disease ontology representing the domain knowledge specific to Alzheimer's disease," *Alzheimer's Dement.*, vol. 10, no. 2, pp. 238–246, Mar. 2014, doi: 10.1016/J.JALZ.2013.02.009.

[52] E. Younesi *et al.*, "PDON: Parkinson's disease ontology for representation and modeling of the Parkinson's disease knowledge domain," *Theor. Biol. Med. Model.*, vol. 12, no. 1, pp. 1–17, Sep. 2015, doi: 10.1186/S12976-015-0017-Y/FIGURES/6.

[53] M. Josefiok, T. Krahn, and J. Sauer, "A Survey on Expert Systems for Diagnosis Support in the Field of Neurology," *Smart Innov. Syst. Technol.*, vol. 39, pp. 291–300, 2017, doi: 10.1007/978-3-319-19857-6_26.

[54] A. A. Al-Hajji, F. M. AlSuhaibani, and N. S. AlHarbi, "ONLINE KNOWLEDGE-BASED EXPERT SYSTEM (KBES) FOR PSYCHOLOGICAL DISEASES DIAGNOSIS," *Comput. Sci. & Inf. Technol. & IT)*, pp.

57–71, Jan. 2019, doi: 10.5121/CSIT.2019.90206.

[55] A. Boujelben and I. Amous, "Refining Rule Bases for Intelligent Systems: Managing Redundancy and Circularity," *Lect. Notes Bus. Inf. Process.*, vol. 389 LNBIP, pp. 421–433, Jun. 2020, doi: 10.1007/978-3-030-53337-3_31.