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Study of the Computer-Based Interventions for Adolescents in the Prevention and Treatment of Depression and Anxiety

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Abstract: **-** There is a growing interest in using digital technology to assist and enhance the psychological health of adolescents, and there is a growing sign that these techniques are beneficial. Co-design is a process that involves the lively participation of investors and clinicians from the standard methods that are used in the creation of interventions.

Objective: This review is to regulate the applicability of computer-based interventions for adolescents with psychological disorders like anxiety and or depression. A literature study and analysis of current intervention technology practices for adolescents were conducted..

Methods: Databases including Medline, PsychInfo, and Web of Science were examined, along with recommendations, reviews, and reference lists. Subsequently, key elements of co-design relevant to practice were identified and extracted. Additionally, case studies and methodologies reported by active investigators in the field were incorporated. A preliminary review encompassing 11 papers and a detailed review comprising 22 papers within the domain were completed.

Results: Topics that are discovered through review are the values of co-design ways of including and attracting a variety of researchers with the difficulties associated with co-design.

Conclusion: Our findings highlight the tremendous benefits of employing computer-based therapies for sadness and anxiety. There is a shortage of evidence to guide the co-design of computer-based gadgets that can help adolescents recover their psychological health. The findings of this study show the need for more research initiatives to improve functioning and clinical symptoms.

Keywords: Psychological health; co-design; depression; anxiety; computer-based intervention, adolescents

I. INTRODUCTION

The majority of. adolescents who struggle with issues related to their psychological health do not receive any type of assistance. Digital psychological health knowledge (i.e., funds and treatments to care for and promote psychological health) have been highlighted as a viable means to expand both reach and access to therapies while maintaining a comparatively low operation price. There is a rising sign to care the use of about technology, with recommendations advocating, for instance, digital Cognitive behavioral therapy (CBT) for depression. This is one example of a condition that may benefit from the use of certain technology ("NICE", 2019).

Furthermore, even in countries with low and moderate resources, a sizable portion of adolescents have accessed the internet and mobile devices. The low level of operator involvement, acceptance, and devotion to this programming in contexts other than research, however, is one of the biggest challenges facing this subject. The number of publications offering general guidance for the development of treatments has increased during the past several years. The guidelines about digital health are indicative of a more comprehensive approach toward the growth and evaluation of health interferences. The standing of the growth stage and user participation at the outset of the process are emphasized in this manner.

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Codesign is a method that involves "collective creation" or "partnership" through prospective operators and investors, who are aggressively engaged throughout the whole growth of the skill. This helps to guarantee that the technology satisfies the requirements and preferences of the user. It is more probable that an interference that is sing-based, busy, satisfactory, and practicable to execute will be produced because of a rigorous procedure that involves users, applicable concepts, and investigative indication. While the notion of co-design in digital health guidelines and literature on how this might be accomplished most effectively are important, they are not sufficient on their own.

To implement co-design, expert-led growth work must abandon its traditional methodology, which produces interferences "for" rather than "with" children and youth. The use of adolescents in design and creation contributes to the "humanization" of numerical technology, a field that has been under fire from some for being overly rigid, rigid, and unresponsive. adolescent is employed in the processes of developing and producing. Factors must be considered while developing technology for adolescents' psychological well-being; this technology should not only be modified by "adult programmers." A developing or age-appropriate approach is needed when it comes to the structure and content of a programmer, as well as considering the diverse variety of interests and preferences held by adolescents.

The manifestation and action of psychological well-being problems in kids and beginning persons vary from those seen in adults in both respects (WHO, 1993) In this work, we provide a consultant evaluation of the progress and strategy processes for digital psychological health and related technologies. This study was carried out in partnership with adolescents and other stakeholders. For the co-design with adolescents, we will create a map of the existing sign and practice, and we will use case education and examples to exemplify the main opinions throughout. The review provides both practitioners and researchers with an impression of a developing investigative area, and it completes with practice points that can help leaders in the preparation, reportage, and examination of codesign doings.

The key part of this paper is to analyze the present knowledge about depression and anxiety amongst youth and evaluate and study existing computer-based interventions from a strategy viewpoint, need to find answers to the research questions:

RQ1: What are the methods for the plan and growth of digital psychological health technology?

RQ2: How much does the present research in depression, anxiety, and technological state of the art from ML, DL, and NLP align with future scope?

II. Preliminary Review

From 2012 to 2018, a wide range of research publications were obtained from the study listed below; however, papers from other domains were excluded. The publications from numerous journals that fit into the categories or topics were gathered. IEEE, Springer, ACM, and other medical journals are among the publishers of the selected papers. For the survey, journals from diverse publishing years were collected. A comparative analysis of multiple articles was conducted to better understand or identify the approaches and strategies followed by different writers. First, we will examine the key concepts relevant to our topic.

A. Key Concepts

Mental health conditions is one of the important human disabilities. Mental illness affects the mind or brain also the way a person thinks, feels, and acts, which include more common disorders like bipolar disorder, depression, schizophrenia, anxiety, and personality disorders [1].

- Mental Health

A condition of emotional health in which a person can live with others, use their cognitive and affective faculties, and fulfill the regular requirements of daily life [2].

- Mental Illness and Vulnerability

A condition when a person's mental health is compromised to the point that it affects their thinking, feelings, and behavior to the point where it interferes with their day-to-day activities. It does not always imply that they require medical attention or that they have a diagnosable mental illness. Mental illnesses are thought to arise from the interaction of genetic vulnerability and stress in life [3].

- Mental Health Team

This group of mental health professionals collaborates in a community context. Psychiatrists, nurses, therapists, caregivers, psychologists, and social workers are frequently among them [4].

- Early intervention

A method for spotting the early indicators of mental health issues and acting quickly to eliminate risk factors in people. People who receive early intervention can recover more quickly and prevent their problems from getting worse [4].

- Depression and Anxiety – mental disorders

Depression- Low mood, loss of interest, feeling of helplessness and worthlessness, guilt exhaustion, disturbed sleep and appetite, reduced communication, and socialization.

Anxiety- excessive worrying about trivial matters, restlessness, numbing sensation, and irrational fear.

B. Preliminary Investigation

The preliminary investigation was carried out through 16 articles given in Table I in detail in several research areas by considering the following objectives for the study.

- Mental health illnesses and their impact on work.
- Depression and anxiety-related work domains.
- The need of early detection and management for depression and anxiety.
- Age groups struggling with sadness and anxiety.
- Psychological therapy and counseling, both online and offline.
- Therapeutic apps and chatbots.

III. LITERATURE SURVEY

From the preliminary review, the literature survey is narrowed to only the papers based on the major objectives of the review. The search criteria for depression, anxiety, and interventions for quality-of-life impairments have been expanded to include papers from 2014 to 2022. The review also includes the papers on the meta-analysis and systematic review.

TABLE I. COMPARATIVE STUDY OF PRELIMINARY REVIEW

Reference Paper	Mental Illness/ Disorder	Measurement Parameters	Measured Artifact	Technical details	Future scope
Calvo et al., 2017[1]	Detect people with mental health problems and aid.	Demographic, lexical, behavioral, and social features	Text analysis from diaries, Twitter, Facebook, blogs, or social websites	1 Dataset with mood and suicidal intent 2 Text classification and Natural Language Processing (NLP)	The ethical ramifications of being able to recognize those in need have not been discussed.
Laske et al., 2015[2]	Alzheimer's disease and for early detection	Cognitive and noncognitive	Progressive memory loss, gait, pupil light response, retinal	A Possible Screening and Diagnostic	Tools in large-scale ongoing clinical trials should be investigated.

Reference Paper	Mental Illness/ Disorder	Measurement Parameters	Measured Artifact	Technical details	Future scope
		diagnostic measures	vasculature, olfactory function, speech, EEG, MEG.	Approach Algorithm is used.	And the utility of the algorithm or revision
Gupta et al., 2014[3]	Predicting depression levels and affective Dimensions.	Method for selecting features based on linguistic, visual, and auditory cues. Variations in people's affective states, such as dominance, arousal, and valence, on a moment-to-moment basis.	To find the best collection of features predictive of depression, various feature selection techniques, and derived visual, auditory, and text-based cues are used. AVEC dataset is used.	1Behavioural Signal Processing 2 Combining frame-wise forecasting across several modalities 3 Support Vector Regressor (SVR) utilizes a normalized polynomial kernel of second degree.	Need to increase the number of samples of correlation between depression severity and affective state. Non-linear algorithms are used.
(Poonkodi et al., 2016[4]	Estimated level of Depression (Chronicle) and for age group 18-33	Features from phone statistics like phone usage frequency, duration, location variance, homestay,	Self-reported survey and Phone usage features	1“Mind at ease” android application to collect user data. 2 PHQ-9 survey. 3 Standard feed-forward backpropagation. 4 Neural Network	Need to include IOT in monitoring sleep time and active time and effective transmission of data to physician side.
Joshi et al., 2013[5]	Depression diagnosis and monitoring to support clinicians and sufferers	Fundamental frequency(f0), loudness, intensity, MFCC13-Audio, Video-intra facial muscle movement, movements of the head and shoulder	Audio, Video and fusion of them	Used open-SMILE, Hamming window, Non-linear SVM Classifier, clustering for STIP of video, LBP-TOP of video.	Can be done for laptops with cameras and microphones and for sensing approaches with mobile, tablets.
Luz et al., 2018[6]	Alzheimer’s Type Dementia With Accuracy 86.5%	Speech rate, turn-taking patterns, grammatical components, richness of vocabulary, complexity of syntactic, psycholinguistics, information	Spontaneous spoken language, content-free features, exploring patterns of dialogue, focuses on the interaction patterns	Logistic Regression	Need to allow for larger datasets with analysis of verbal and non-verbal (e.g. facial) parameters while taking spontaneous dialogue

Reference Paper	Mental Illness/ Disorder	Measurement Parameters	Measured Artifact	Technical details	Future scope
		content, repetition, acoustics, coherence of speech, and prosody.			
Lee et al., 2012[7]	Differentiating the neurophysiological traits of MDD and ADJ	Quantifiable analysis of an electroencephalogram, power and coherence, brain activity, EEG recording from different sites	Electroencephalogram (EEG)	Fast Fourier transform algorithms are used	Uncover the temporal change in the characteristics of QEEG before and after treatment
Abdullah & Choudhury, 2018[8]	Not specific disorder but for in general Mental Health	Tracking Social, physiological, and behavioral signals,	Sensors for phone and wearables devices.	Scalable technologies	1. The need to close the gap between conventional therapy and sensing technologies 2. Think about engagement, adherence, privacy, confidentiality, validity, and efficacy. 3. Multimodal data stream integration may increase classifier accuracy.
D. Zhou et al., 2015[9]	Demonstrates the relationship between the collected multimodal signals and mental states	An examination of a user's social media activity to determine their mood and emotions, as well as heart speed rate and other parameters	Social media interactions on the internet, physiological signals picked up by widely used sensors, captured through webcams in mobile devices like laptops, tablets, and smartphones,	Used computer vision and signal processing techniques, machine learning techniques to build a model, Sentiment analysis of social Media content, behavior Science	1 can be used as a technique to evaluate people's affective states on a broad range. 2 More precise depression scale utilizing the dynamics of facial expressions is required.
X. Zhou et al., 2018[10]	Predict Depression (MDD) severity	Facial Image	Cropping, eye position alignment, resizing,	Deep convolution neural Network for feature extraction and regression classification,	Can enhance the general prediction performance of depression data from audio, video, and facial

Reference Paper	Mental Illness/ Disorder	Measurement Parameters	Measured Artifact	Technical details	Future scope
				AVEC 2013 and 2014 dataset with video corpus, ML toolkit DLib.	dynamics, depression recognition
Valenza et al., 2014[11]	Bipolar Disorder	Both physiological and behavioral There are parameters, DSM IV criteria for depression, hypomania, mixed state, and euthymic state.	Digitalized questionnaires, voice analysis, digital agendas, cardiac activity via a smartphone and t-shirt, and the PSYCHE project	Embedded electronics and smartphones, centralized server, advanced signal processing algorithms, remote server, ML algorithms	Can be used this technology for any other disorder

A. Literature Search Strategy

The following databases: National Library of Medicine PubMed Central, Scopus, BMJ Journals, and PsycINFO were used for the comprehensive, computerized literature search. The studies under consideration include ones that have appeared in reputable journals like BMJ Open, Health Psychology and Behavioral Science, Journal of Medical Internet Research, Innovations in Health Informatics, Health, and Technology, NPJ Digital Medicine, etc. Each database was searched from 2014 to 2022, regardless of when it was published. The search terms used were "Depression" AND "Anxiety" AND "Intervention" OR "mental health". Using a similar criterion as machine learning, the element (data mining) was sought out. In cases where the entire text was not accessible, the essential details were gathered using the abstract to prevent selection bias.

B. Included trials

388 original bibliographic references were screened. The flowchart (Figure 1) shows which trials were included and why they were not. 41 of the 388 papers were excluded due to duplication. Age, development studies, other studies, language, type of disorder other than depression and anxiety, type of work as in detection or intervention, and intervention mechanism as offline or online were among the reasons for the exclusion of 145 papers out of the 347 that remained. Out of 202, 151 full texts were available. Out of full-text articles, 56 articles on depression anxiety, computer-based interventions, and technological usefulness as the use of Machine Learning (ML), Deep Learning (DL), and NLP are included in the study. Then after analysis of all the articles from the perspective of applicability, design, algorithmic techniques, effectiveness, evaluation, and systematic reviews 22 articles are more applicable and in the final detailed discussion of the review.

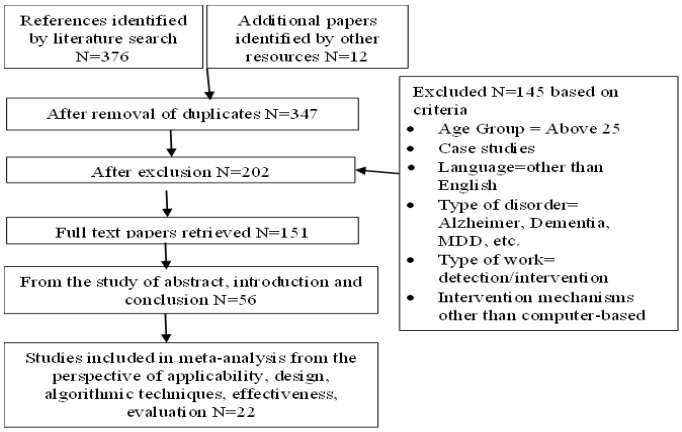

Figure 1. Study Flow

Many of the initiatives which as "intervention." Studied with privacy of the participants. Ethics, legality and rights etc. were concerned.

C. Included Studies and Detailed analysis

First duplicates are removed then the other two authors independently examined all headings and abstracts applicable to this review. We choose only English-language studies. We purposely ignored some studies to emphasize articles examining the therapeutic use of NLP and ML in psychiatry. Publication dates were not restricted in any manner.

The detailed investigation of the papers in computer-based interventions for youth with psychological disorders like anxiety and depression is completed with 22 papers and given below. The study is useful to improve the research in this field and to understand more insights for research. Each study's key findings are reported in a separate table after being carefully vetted. The tables offer details on quantitative and qualitative characteristics, including author and publication details.

Danbi Yang et al., (2018)[12] carried out a meta-analysis to investigate the potential benefits of online treatment programs for individuals experiencing depression and other quality-of-life impairments. The average impact of web-based therapy on the severity of symptoms associated with depression was 0.72. On the other hand, the investigation into the effects of computer-based treatments on excellence of life did not yield satisfactory results, in contrast to the finding that indicated a medium to high impact size.

Our results suggest that using Internet-delivered therapies for depression symptoms may have significant benefits. However, it was found that these relatively new intervention techniques were insufficiently effective for individuals who suffer from notable declines in their quality of life. The discovery of this academic work emphasizes how important it is to keep looking into the creation of web-based intervention techniques that could aid people suffering from psychological disorders in improving both their overall functioning and their clinical symptoms.

Piers Gooding et al., (2020) [13] have proposed a goal to conduct a literature review on algorithmic and information-driven skills that are utilized in online psychological health therapies with the end goal of identifying the legal and ethical concerns that have been created because of these technologies. The results were organized into the following 5 groups of knowledge: social broadcasting (numbering 53), cellphones (numbering 37), detection skill (numbering 20), ‘chatbots’ (numbering 5), and other/various (numbering 17). Most efforts were geared at something called "detection and diagnosis."

In the popular studies, discussions of privacy were absorbed mostly on how to protect the privacy of study participants, with only a little amount of time devoted to discussing privacy about its setting. Only 19 out of the total number of research addressed the issue of ethics as an explicit topic of concern. Concerns that have been brought to our attention include the almost total absence of input from facility users, the little thought of "algorithmic responsibility," or the chances for over-medicalization and techno-solutionism.

Most of the articles that were published in computer science were either exploratory or pilot studies. As a result, these skills might be taken into repetition in ways that are seldom recognized, which could have major repercussions for both the law and ethics.

Judith Borghouts et al., (2021)[14] suggested a systematic study to categorize common obstacles and facilitators that affect users in engaging DMHIs. A total of 208 articles met the inclusion requirements. A variety of research methods, including meetings, surveys, attention gathering, shops, field studies, and operator evaluation analyses, were employed in the featured publications.

The analysis identified three main categories of factors involved in the coding process: content, program, and end user supplied by the intervention, as well as the environment of the skill or application. Three typical obstacles included technological challenges, significant psychological health issues, and a lack of personalization. On the other hand, increased social connectivity, enabled by enhanced health awareness and a feeling of self-management, emerged as common facilitators. Mario Alvarez-Jimenez et.al., (2020)[15] have introduced a method known as co-design, aimed at ensuring that digital technologies align with the preferences and priorities of their end users. The objective of this approach is to enhance the realism, attractiveness, feasibility, and satisfaction of these technologies. Co-design is a versatile method applicable at any phase of a skill's life cycle, including creation, evaluation, and implementation, and across various research levels. Engaging children, teenagers, and other stakeholders in the co-

design process can be achieved through various means. Future research in this field should consider the evolving nature of technology, the diverse range of user demographics, the imperative of disseminating findings more broadly, and the significance of the co-design process.

A. S. Neilsen (2019) [16] has proposed a comprehensive literature review aimed at gaining a deeper understanding of the integration of Human-Computer Interaction (HCI) principles and user-centered design in the development of online interventions, and how these interventions are subsequently reported in literature to inform evidence-based practice.

The PRISMA framework was employed to select the 30 most relevant articles. The primary discovery of this review is that online health interventions are often deployed without adequately elucidating the fundamental aspects of HCI design. This deficiency raises concerns about the credibility of evaluations of e-psychological interventions. Chang Su et al., (2020) [17] have proposed a work that aims to conduct a literature appraisal on the many uses of DL algorithms that have been studied in the context of psychological health outcome research. To be more specific, we begin by providing a high-level review of the most recent developments in DL approaches. After that, we will do a literature study on the topics pertinent to DL applications in psychological health outcomes. In this work, we examined earlier research on the application of DL to examine psychological health effects and analyzed the results. The information contained in all the publications that were reviewed for this study serves as an example of the applicability and promise of DL for improving the identification and management of patients with mental health issues.

Y. Tyshchenko (2018) [18] has conducted a study, that uses an experimental psychological approach to the gathering of data to compile a body of blog entries written by clinical participants as well as control individuals.

Clinical subjects are individuals who have been diagnosed with a disease, while control subjects are healthy persons. To analyze the content of the blog according to the issues discussed by its writers, we examine the hidden topics that are uncovered in the gathered data. We experiment with several different methods of text encoding and the properties of topic models. To differentiate between clinical and control participants

We use CNN and SVM classifiers. In addition, we investigate the classification performance of Convolutional Neural Networks (CNN) after they have been trained on texts of varying lengths taken from blog posts. CNN classifier that was initialized with pre-trained “GloVe word vectors” had the highest levels of correctness and recall, with respective cuts of 78% and 0.72. The primary goal of it was to extract the blogs in such a way that the subjects discussed on them would not be reliant on the control corpus or the clinical corpus.

Still, prevention and health are not given enough attention. Presumably, the main references for developing mobile results related to psychological health are to shift toward social and technical design strategies, comprehend and generate shared value, identify all facets of effectiveness, link project and medicinal study and growth, and adopt an ecosystem viewpoint.

Asra Fatima et al., (2021) [19] have proposed a research paper that provides a model for semi-supervised machine learning that we call DASentimental. Its goal is to identify Texts that talk about depression, stress, and anxiety. This was done to learn more about how people store information in their memories. This gives items on the BOW weight based on how important they are to semantic memory. Additionally, it guides memory using semantic network distances, which aids in integrating memory into a cognitive picture. This embedding yielded contemporary, predictions for stress, anxiety, and depression with the R values of 0.52, 0.44, and 0.7, which were consistent with earlier findings utilizing additional human data.

With the help of DASentimental, a neural network driven by a multilayer perceptron, it is now possible to investigate the organizations of expressive discomfort. We discovered that the semantic detachments between recollections, also known as walk coverage, were critical for evaluating degrees of sadness but were unnecessary for calculating levels of worry and stress. When the "sad–happy" dyad was taken into consideration, the predictive power of semantic distances from "fear" was nullified since they were unnecessary.

Emily G Lattie et al., (2019) [20] have proposed a study to do a literature review on Digital Mental Health (DMH) interventions that helped students with depression, and anxiety, and improve their mental health. This was done to find out how effective, usable, acceptable, taken up, and adopted these programs were. The interventions were mostly about depression, anxiety, and improving mental health.

The vast mainstream of treatments (71 out of 89, or 80%) was provided via the use of a website, with internet-based cognitive behavioral therapy being the majority (28 out of 31%) of all therapies. A significant number of programs (33, 37%) included some type of human assistance, namely coaching. Most interventions were either successful (42, 47%) or somewhat successful (30, 34%) in terms of causing favorable shifts in outcome variables. The results suggest that digital psychological health interventions may help college students with their depression, anxiety, and overall mental health. However, more thorough research is needed to find out which parts of these interventions work.

Martin Harter et al., (2018) [21] have proposed a project with the objective is to organizing the available signs of traumatic brain injuries about the various phases of depression organization and evaluating the efficacy and acceptability of treatment for each scientific stage while considering both active and inactive (such as waitlist) controls as comparisons. Only randomized controlled trials will be taken into consideration, and these will be found through extensive searches of key databases of Controlled Trials from Cochrane Central Register “PSYNDEX”, Medline, “CINAHL”, and “PsycINFO”, clinical trial registries and grey literature.

David T. Parry et al., (2016) [22]conducted an extensive investigation to determine the methodologies employed in evaluating the in-person psychological experiences of individuals who have undergone self-help psychosocial therapies via the Internet. A comprehensive literature review was conducted across various disciplines, with a particular emphasis on computer science and health.

Studies meeting specific search criteria were considered for inclusion. Among the 21 identified studies examining the psychological experiences of users, only one collected data on user experiences during product usage. The predominant methods used to gain insights into users' experiences were semi-structured interviews conducted post-treatment and questionnaires distributed after intervention sessions. There is a paucity of approaches that have been specifically outlined in the research that has been done to assess the interface that users have with Web-based psychological health or behavior change artifacts. The importance of the issue and the cross-disciplinary character of the area were two of the most significant limits of the study. Methods of analyzing the psychological experiences of users when they are using an intervention need to be developed and implemented as soon as possible.

F. Alqahtani et al., (2020)[23] have suggested conducting a study to examine user assessments of psychological health applications that are available to the public. This will help to determine the advantages, disadvantages, and gaps in the applications, as well as the reasons why users discontinue using them. After mining reviews of 106 psychological health apps, we applied theme analysis to 13,549 reviews that we downloaded from Google Play and the Apple App Store. These evaluations were taken after the corresponding app stores. The examination of the reviews shows that users are more concerned with the app's usability and user interface.

Apps that provide users with a selection of features, functions, and materials from which to pick are also well-received by users. Again, applications that provide adaptable functionality that enable users to alter certain app aspects earned excellent ratings. These kinds of apps give consumers more control over the app. On the other hand, a bad user experience emerged as the primary reason why people stopped using psychological health applications. Other drawbacks include an absence of a diversity of material, an absence of customer service, a lack of personalization and trust, as well as concerns over security and privacy.

Ruvan Weerasinghe et al., (2019) [24] have conducted a comprehensive analysis of the published research on ML and NLP techniques in the diagnosis of depression in online forums and groups. A thorough search was carried out to locate studies that investigated the use of ML and NLP strategies to recognize symptoms of depression based on support group data. The PRISMA methodology was used to choose the articles that were considered. To carry out the review’s objectives, a total of 29 papers were chosen and analyzed.

Based on this comprehensive study, we conduct further research to determine which combinations of characteristics obtained from ML and NLP approaches are efficient and remarkable for modern Depression Identification. In conclusion, we will discuss some unresolved challenges that continue to impede the actual deployment of such systems in the real world, and we will indicate the way toward potential future research in this area. In addition, this research investigated the efficacy of the textual hints found on open support forums about depression. This study reveals that just a small number of research has been undertaken to investigate how social, physical, and emotional behaviors impact human psychological well-being.

There is a serious issue here. Furthermore, as we discussed in the previous section, our research may contribute to the development and validation of novel classification models in the future that will be used to recommend, in real-time, individually tailored interventions for users participating in online support forums depending on depression disorder level. Recommendations based on these models might be given to users of online forums for assistance.

Taylor C Ryan et al., (2021)[25] have proposed a systematic review with the primary objective of elucidating and defining, both operationally and practically, research utilizing Machine Learning (ML) and Natural Language Processing (NLP) approaches for psychological health. The secondary aim was to assess the feasibility of employing these methodologies in medical settings pertaining to psychological health. The investigation involved searching four distinct medical databases, including PubMed, PsycINFO, BMJ, and ScienceDirect, utilizing keyword combinations such as machine learning, psychiatry, data mining, psychological health, and disorders. In terms of the methodologies that were used, the preprocessing stage made use of the conventional NLP and unique identifier extraction strategies that are designed specifically for use with medical texts. Instead of classifiers that functioned transparently, it was recommended to use efficient classifiers. Python was the platform that was used most often. Many language traits can boost the effectiveness of NLP approaches; the extent to which these features may be extended to other languages should be examined more thoroughly.

On the other hand, methods such as ML and NLP may extract related information from data that has not previously been investigated (for example, the daily routines of patients, which are often unavailable to medical professionals). There are still ethical questions that need to be answered before considering it as a supplementary tool for the treatment of psychological illness, and these questions need to be addressed as soon as possible. It is possible that machine learning and NLP approaches may give numerous views in the field of psychological health research; nevertheless, these technologies should also be seen as instruments that will assist therapeutic practice.

Adrian B. R. Shatte et al., (2018) [26] have swiftly mapped the area of machine learning in psychological health, we used an approach called a scoping review. There was a total of eight research databases from the related areas that were examined for articles on this topic. Two different reviewers examined each publication, and data were gleaned from each one about the article's applicability to psychological health, ML approach, data type, and research outcomes.

Depression, Schizophrenia, and Alzheimer's disease were the most frequent forms of psychological illness that were treated. Support vector machines, Latent Dirichlet Allocation, Neural Networks (NN), Decision Trees (DT), and clustering were some of the ML algorithms that were used. In general, the usage of ML in psychological health has shown a diversity of improvements in diagnosis, therapy, support, research, and clinical administration. These benefits have been proved across all these fields.

Stevie Chancellor et al., (2020) [27] have studied that intensive care, diagnosis, and intervention plan for various psychological health states stand to gain a great deal from this study, as it promises to do so. However, there is no such standardized approach and methodologies for assessing the validity and design of this research study. This is a major limitation in the field. We undertake a comprehensive literature assessment in guessing mental health position using social media data, with a particular emphasis on features of the study design, research methodology, and methodological approaches. There were seventy-five papers published in this field between the years 2013 and 2018, according to our count. Our findings provide an overview of the processes involved in data interpretation for psychological health status, data collection, preprocessing and feature-model selection, verification, and so on.

Despite the increased curiosity in this topic, we find some worrying patterns around construct validity, as well as a lack of reflection in the methodologies that are employed to operationalize and define psychological health status.

Nymatul J. Nipa et al., (2020)[28] examined the worth of the data discovered in earlier studies on mobile health interventions using the framework of evolving countries, A thorough search of some of the most reliable databases was done to find studies on mobile health apps that had been released between 2013 and 2018. Thirteen papers in total were chosen for data extraction and synthesis following a rigorous screening procedure based on methodological standards. We offer several noteworthy and intriguing discoveries. First off, there is a dearth of knowledge regarding health using writing and valuation lists among the scholars and intervention creators involved in mobile health in developing nations.

Adil Rajput (2020) [29] has investigated the numerous current theories that underpin the area of NLP, as well as how those theories might be used to collect the emotions of users on social media. Over some time, such feelings may be eliminated, which will outcome in a decrease in the number of mistakes caused by data entry and other sources of stress. In addition to this, we investigate the use of sentiment analysis and NLP in the field of psychological health.

The reader will also get an understanding of the NLP ToolKit (NLTK), which is a collection of programs that help put different NLP ideas into practice, and how these programs may make the process of data scavenging much simpler. In addition, we have included a concise summary of the benefits that may be gained by using the Python programming language with the NLTK toolbox. In conclusion, we have discussed a variety of applications within the area of sentiment analysis, as well as applications of NLP within the medical profession. The author hopes that in the not-too-distant future, sentiment analysis will be used to support the finding of psychological well-being problems such as cyberbullying and depression.

K. Zeberga et al., (2021)[30] have proposed a novel framework in this paper to identify posts related to psychological health efficiently and effectively while maintaining the meaning of the words when applying bidirectional encoder representations. Specifically, our goal is to achieve this while preserving the meaning of the words.

In addition, we suggest a methodology known as knowledge purification, which is a relatively new method of information transfer from a pre-trained model of BERT to a more compact model to improve evaluation and precision. In addition to this, we developed our system for the harvesting of data from the most popular social media sites, which include Reddit and Twitter. In the end, we used word2vec in conjunction with BERT and Bi-LSTM to efficiently evaluate and recognize indicators of sadness and anxiety in social media postings.

Using the knowledge distillation methodology, our system achieves an accuracy of 98%, making it superior to other state-of-the-art systems. In addition to response-based knowledge refinement based on the neural response of the last output layer in BERT, the proposed BERT-based model turns the gathered words into vectors to capture the semantic meaning from the text corpus to boost classification accuracy.

This was done to construct a model that is both more compact and more intelligent for the analysis and classification of depression and anxiety. The data set is prepared from Twitter and Reddit with the relevant text data to build a smart healthcare system. This was accomplished by using a combination of NLP and data mining techniques. Finally, we carried out a comprehensive experiment, the results of which demonstrate that the suggested BERT Bi-LSTM model enhances the precision of sentiment categorization based on posts.

Franziska Burger et al., (2020) [31] have done literature analysis which focuses on three primary research issues to provide an outline of the scenery of e-psychological health systems for the treatment and prevention of the major depressive disorder.

(1) What different kinds of systems are there?

(2) To what extent do these systems make use of modern technology?

(3) What kinds of changes have been made to the system landscape since the year 2000?

Furthermore, autonomous systems—that is, systems without human guidance—are just as technologically sophisticated as guided systems, despite having a third fewer features. As a result, neither the lack of direction nor its lack of direction is made up for by increasing the number of functions or their level of technological advancement. The average system falls somewhere between being purely informative and being one that accepts data input but does not automatically analyze it, even though a variety of high-tech solutions might be created.

R. Grist et al., (2018) [32] have investigated the current state of study on the usefulness of online-based therapies for treating anxiety and depression to update earlier studies in this field. Overall, the study's findings support the notion that wait-list controls for anxiety and depression behave less successfully than CBT-based technology-delivered therapies. Compared to the control groups, CBM and "other" programmers were unable to demonstrate a discernible improvement. The intervention based on ABMT yielded a minimal effect size.

Ana Fonseca et al., (2021)[33] suggest that for young people to benefit from interventions, prerequisites such as a good relationship with a doctor and appropriate parental supervision are necessary. They highlight the advantages of using ICTs in psychological health research for practitioners and scholars. Additionally, they discuss various

strategies to address challenges in the field, particularly the inability to assist all individuals in need from a clinical perspective (prevention, promotion, and treatment).

IV. Outcome of the Survey

The preliminary review to acquire the domain knowledge and for interdisciplinary study is conducted with 16 papers as given in Table 1. Following that, 388 original bibliographic references were reviewed. The flow chart (Figure 1) shows which trials were included and why they were not. Finally, the meta-analysis of 22 studies conducted with summarization.

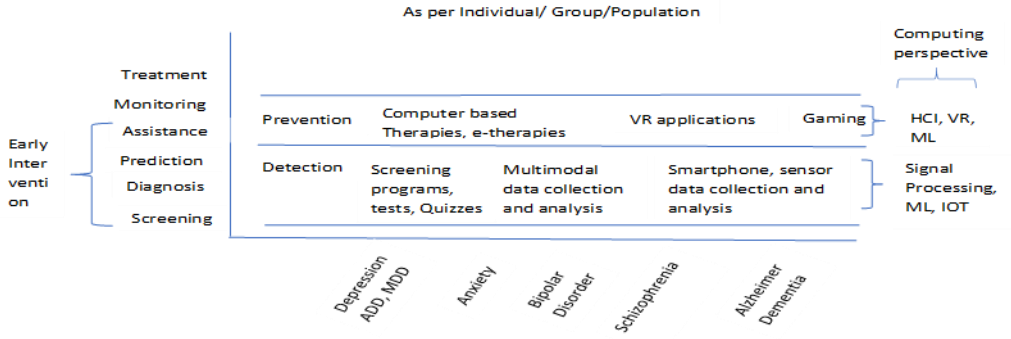

Figure 2. Collaboration of Technology with Mental Health

The first review finding is summarized as in Figure 2, which shows the collaboration of mental health and technology. For mental wellbeing of person as individual, group or population, it must go through different phases as screening, diagnosis, prediction of severity, assistance, monitoring and if required treatment. Early detection and intervention are very important for patient in which technology plays major role. The first major step, detection includes the different techniques like screening programs, tests, quizzes, multimodal data collection or use of smart-phone and sensors for data collection, which can be implemented with the use of

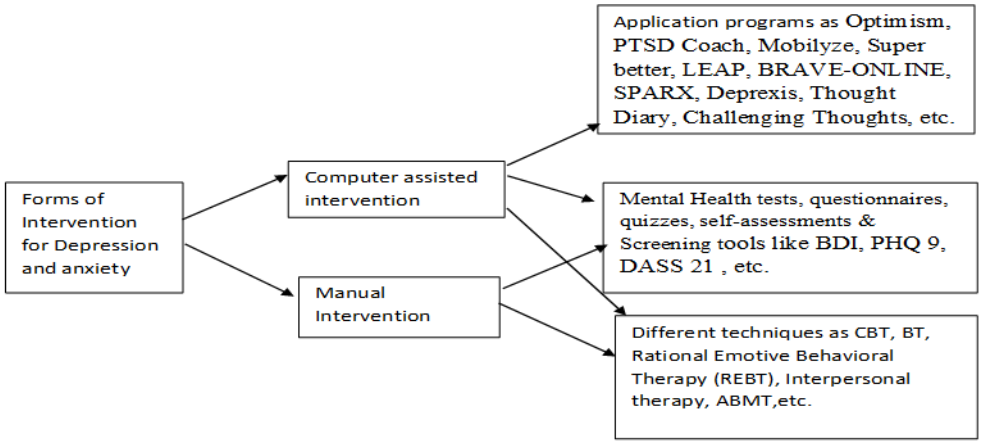

Figure 3. Wellbeing Programs for Depression and Anxiety

technologies as Signal Processing (SP), ML, AI, Big data, Internet of Things (IOT). Next major step is providing intervention so that the mental health will be better, can be handled with different techniques as computer-based therapies or e-therapies, Virtual Reality (VR) applications, gaming etc. by using technologies like HCI, ML, and AI.

The second review finding states that the primary literature focus is on finding severity of depression, anxiety and improving its accuracy whereas others focus on providing online intervention for depression and anxiety [34][35]. If we will do early detection of the problem and provide an intervention for early stage, it will be more helpful for society. HCI has more scope in an effective online or computer/mobile assisted intervention. Figure 3 shows the

different techniques, application programs and questionnaires used in manual and computer assisted intervention programs

Online Interventions mainly use CBT for depression and anxiety with or without randomized control trial, and therapist assistance[36]. CBT has much more efficacy but has some of the limitation with use in online interventions. Drop-out rates is a major challenge. The different factors like control condition, severity of illness, type of support and other treatments affect efficacy of the online intervention [37].

Effects of computer-based interventions on depression and anxiety

The computer-based intervention meta-analysis found that the mean impact size was significantly different. Based on a random-effect model, the results showed notable heterogeneity between the studies in terms of indication of heterogeneity and the fixed-effect model-based meta-analysis found a difference in quality of life that suggested the web-based intervention was superior. Given the modest heterogeneity observed, the difference in the treatment effect on quality of life was computed using a fixed-effect model.

V. CONCLUSION

The examination of existing research revealed a scarcity of design information in the literature concerning e-psychological health treatments. This deficiency is particularly concerning as it impedes the replication of e-psychological health intervention studies. Additionally, it poses challenges in validating the effectiveness, quality, and safety of treatments proposed for online management of anxiety and depression. Although electronic psychological health interventions commonly incorporate self-monitoring components, insufficient detail is provided to determine the optimal design elements for such interventions. While goal-setting processes are frequently employed, the specific design elements are not adequately documented, hindering the reproducibility of outcomes. These characteristics may impact the clinical efficacy of therapy and patient adherence, underscoring the need for meticulous characterization to facilitate reproducibility in research. Log data studies offer precise insights into the actual usage of components, indicating whether users behave as expected by designers and clinical teams. Despite limitations, our recent meta-analysis provides robust evidence supporting the effectiveness of web-based interventions in reducing depression and anxiety severity. A novel psychotherapy platform enabled by web-based intervention holds promise for enhancing current depression treatment options or serving as a viable alternative. However, it does not fully meet quality-of-life domain requirements despite its potential utility. The meta-analysis underscores the importance of developing a wide range of intervention modules to broaden web-based intervention strategies. Future research should prioritize methodological rigor and practical relevance to offer users valuable guidance.

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