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REVIEW

A Comprehensive Survey on Federated Learning Applications in Computational Mental Healthcare

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ABSTRACT

Mental health is a significant issue worldwide, and the utilization of technology to assist mental health has seen a growing trend. This aims to alleviate the workload on healthcare professionals and aid individuals. Numerous applications have been developed to support the challenges in intelligent healthcare systems. However, because mental health data is sensitive, privacy concerns have emerged. Federated learning has gotten some attention. This research reviews the studies on federated learning and mental health related to solving the issue of intelligent healthcare systems. It explores various dimensions of federated learning in mental health, such as datasets (their types and sources), applications categorized based on mental health symptoms, federated mental health frameworks, federated machine learning, federated deep learning, and the benefits of federated learning in mental health applications. This research conducts surveys to evaluate the current state of mental health applications, mainly focusing on the role of Federated Learning (FL) and related privacy and data security concerns. The survey provides valuable insights into how these applications are emerging and evolving, specifically emphasizing FL's impact.

KEYWORDS

Depression; emotional recognition; intelligent healthcare systems; mental health; federated learning; stress detection; sleep behaviour

Abbreviation

DL	Deep Learning
ML	Machine Learning
FL	Federated Learning
FL-EHR	Federated Learning in Electronic Health Records
IoMT	Internet of Medical Things
mHealth	Mobile Health
EHR	Electronic Health Records
EEG	Electroencephalography
DAIC-WOZ	Distress Analysis Interview Corpus
PTSD	Post-Traumatic Stress Disorder
WESAD	Wearable Stress and Affect Detection
ECG	Electrocardiogram
GSR	Galvanic Skin Response
RNN	Recurrent Neural Networks
Ham-D	Hamilton Depression Rating Scale
HADS scale	Hospital Anxiety and Depression Symptoms
AUC	Area Under the Curve
ResNet	A Residual Neural Network
CNN	Convolutional Neural Network
LSTM	Long Short-Term Memory
ADAS	Advanced Driver Assistance Systems
LR	Logistic Regression
SMOTE	Synthetic Minority Oversampling Technique
DNN	Deep Neural Network
MLP	Multilayer Perceptron
MOS	Mandatory Optimization Strategy
CL	Centralized Learning
SER	Speech Emotion Recognition
N-IID	Non-Independently and Identically Distributed
FER	Facial Expression Recognition
AE	Autoencoder
RAVDESS	Ryerson Audio-Visual Database of Emotional Speech and Song
GRU	Gated Recurrent Units
Bi-LSTM	Bidirectional Long Short-Term Memory

1 Introduction

Mental health is vital for good wellness, even though diagnosis and treatment of mental illnesses are difficult due to their varied complexity. In particular, the application of technology in mental health service provision has undergone considerable improvement in recent times [1,2]. Collaborative machine learning, known as federated learning, can be promising for complex mental health applications [3]. This research will measure and summarize the current landscape of mental health applications in FL.

Typically, in traditional models, mental health centers train models apart within the settings, as illustrated in Fig. 1. Instead, federated mental health learning is a revolutionary strategy [4]. Fig. 2 entails training individual models at different centers and updating the single centralized model with these models. Importantly, this process occurs without sharing raw data, marking a significant shift in privacy preservation and collaborative learning strategies [5].

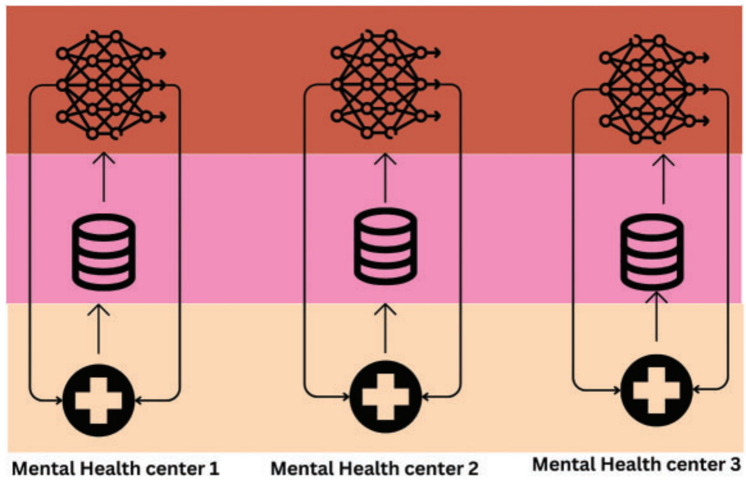

Figure 1: A traditional learning for mental health application

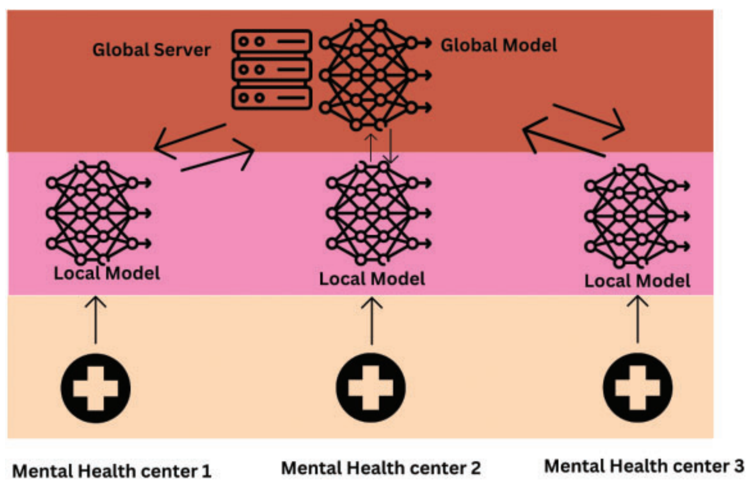

Figure 2: The federated learning of mental health application

This research focuses on federated learning approaches ML and DL in the mental health field to enhance knowledge, diagnosis, and cure of mental health diseases.

This study compares cutting-edge federated learning apps and traditional mental health apps. It aims to conduct a brief analysis focusing on the various facets that define this dynamic industry. By extensively investigating the datasets used, the data sources supporting these apps, and the specific mental health symptoms addressed, this study aims to assess the healthcare industries.

The sources and data types are discussed at the outset of this article's structure. This research investigates federated mental health applications that are categorized based on symptoms. Next, it details how it can theoretically incorporate Federated learning ideas into the proposed Federated mental health system. The processes involved in federated deep learning and machine learning are explored. The following sections describe the advantages of mental health apps. The study concludes by outlining possible directions for the future and providing a holistic view of development for federated learning in mental health applications. This research aims to advance the ongoing discussion over technology compatibility and mental health.

The study's contributions are presented as follows:

- Introduction of Federated Learning in Mental Health: Federated learning embracing complex mental health issues.
- Revolutionary Collaborative Learning Strategy: Supporting a move from the conventional individual sample training model to group cross-center training, maintaining privacy and not sharing raw data.
- Comparative analysis of federated learning applications and traditional mental health apps, datasets, data sources, and targeted mental health symptoms.
- In-depth Exploration of Processes and Advantages: Exploring the mechanisms behind federated deep learning and machine learning that provide an understanding of how they improve the knowledge, diagnosis, and treatment of mental health diseases.

- **The Comparative Study of Federated Learning Surveys in Healthcare**

Table 1 lists several survey papers that explored federated learning in healthcare, and they are viewed from numerous perspectives, such as general healthcare, IoT, EHR, and blockchain, but no work has integrated mental health aspects, which are essential these days. Therefore, this study aims to fill the gap in reviewing the research on federated learning in mental health applications.

Table 1: The survey papers list regarding federated learning in healthcare

Authors	Research summary	IoT	EHR	Blockchain	Mental health
Xu et al. (2021) [6]	• Evaluation of federated learning technology concerns, consequences, and opportunities in the healthcare field.		✓		
Patel et al. (2022) [7]	• Propose a layered healthcare informatics architecture based on federated learning (FL) in electronic health records.		✓		
Ali et al. (2022) [8]	• Survey a healthcare system by applying the internet of medical things.	✓			
Joshi et al. (2022) [9]	• Reviewing existing studies on federated learning within the healthcare industry, emphasizing its use cases and applications.		✓		

(Continued)

Table 1 (continued)

Authors	Research summary	IoT	EHR	Blockchain	Mental health
Dasaradharami et al. (2023) [10]	• Survey of applications for FL for healthcare informatics.	✓	✓		
Li et al. (2023) [11]	• Survey of applying security measures toward federated learning and medical applications.		✓	✓	
Gahlan et al. (2024) [12]	• An overview of emotion recognition systems utilizing physiological signals.				✓
Khalil et al. (2024) [13]	• An overview of federated learning in mental health research.				✓
Our study	• A comprehensive survey about federated learning toward mental health application.		✓		✓

2 Dataset Source for Mental Health Apps in Federated Learning

With a focus on federated learning for mental health applications, diverse data sources are the foundation for understanding, analyzing, and improving mental well-being, as shown in Fig. 3. These sources include:

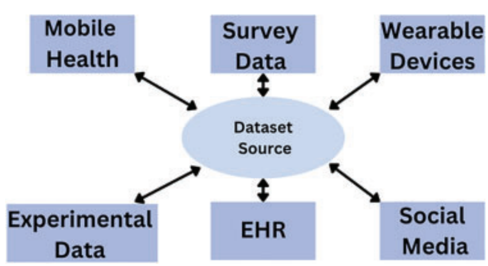

Figure 3: Dataset source information

2.1 Mobile Health (mHealth)

Federated learning for mental health applications depends on mobile health (mHealth) as a data source. People freely provide real-time mental health data through mHealth apps on their smartphones and tablets, providing insightful information while maintaining the privacy and confidentiality of their sensitive data [14,15]. Federated learning integrates data from several mHealth sources to enable cooperative model training for enhanced mental health therapies [16–19].

2.2 Survey Data

Participant surveys are essential to gathering structured data for federated learning for mental health. Machine learning techniques from federated learning can be employed to assess mental health behavior, attitude, and symptom survey data. This ensures that the opinions of various respondents are combined to develop a detailed and protected mental health model [20–23].

2.3 Wearable Devices

Devices like smartwatches and fitness trackers can be dynamic physiological data sources for federated mental health learning [24–27]. They protect individual user privacy, returning *vs.* open-ended monitoring of mental-well-being-linked data. Federated learning utilizes data from multiple wearables to support the training of models in a cooperative manner, delivering personalized insights without centralizing sensitive data [28–30].

2.4 Electronic Health Records (EHR)

The wide-ranging data sources of electronic health records significantly support federated learning-based mental health applications. Federated learning helps to integrate knowledge from different EHR data sources for a more inclusive understanding of a person's treatment plans and mental health history. Therefore, this strategy promotes precision in mental health interventions [31–34].

2.5 Social Media Contributions

Social media sites as sources of mental health data in federated learning settings. Trends and attitudes in mental health via social media conversations, knowledge exchange, and community involvement. For example, federated learning enhances the knowledge of mental health in diverse populations by incorporating their contributions collectively and guaranteeing user's privacy [35–38].

2.6 Experimental Data

Experimental data refers to the structured and controlled data generated from clinical trials, laboratory studies, or simulated environments specifically designed to study mental health interventions. Regarding federated learning, experimental data can be used for model training on complex scenarios to capture through mHealth apps, surveys, wearables, or EHRs. This data can be invaluable for testing hypotheses, validating results from other sources, and ensuring that federated learning models can generalize across different conditions and settings. By integrating experimental data, federated learning can contribute to a more robust and comprehensive understanding of mental health, ensuring that models reflect real-world data and are grounded in scientific research. This data is essential for fine-tuning models and validating outcomes from various federated learning processes [39–42].

3 Dataset Type for Mental Health Apps in Federated Learning

Applications related to Federated Learning for Mental Health use many datasets, each offering an individual insight into the complexities of mental health. These datasets are divided into several indications of different methods for understanding and diagnosing mental health, as depicted in Fig. 4.

3.1 Text-Based Datasets

Mental health applications should involve text data such as user-generated content, clinical notes, and textual indications of emotional states. These include text data for sentiment analysis, pattern detection, and relevancy information extraction using natural language processing techniques [43–46]. Fig. 5 illustrates the process of utilizing textual data in a sentiment analysis task.

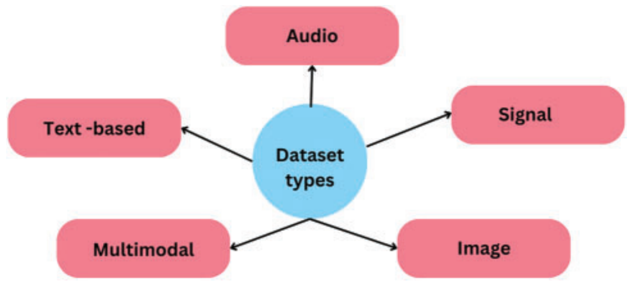

Figure 4: Dataset types information

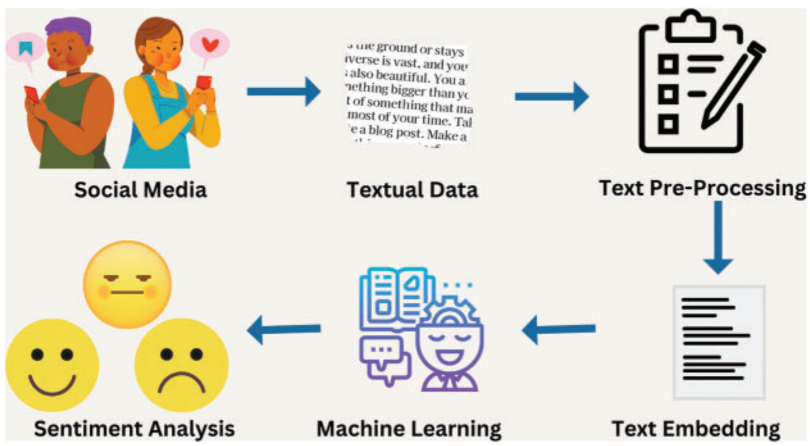

Figure 5: Text data processing using machine learning models for predicting sentiment analysis

3.2 Audio and Speech Datasets

Mental health applications gain auditory dimensions from speech and audio datasets. Tone detection, voice analysis, and speech patterns are helpful ways to determine someone's emotional state. These datasets enable the creation of algorithms that identify and respond to emotional cues in spoken communication [47–50]. Fig. 6 depicts the process of speech signal processing for depression identification.

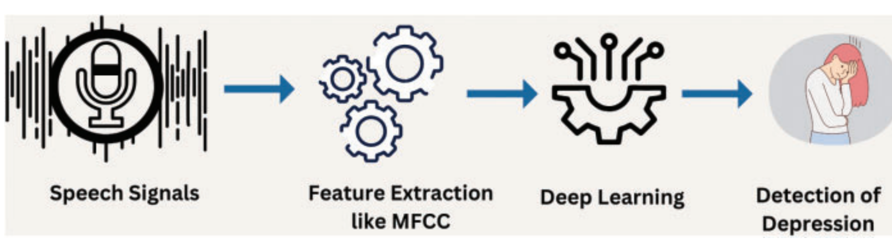

Figure 6: Speech signal processing using deep learning models for detecting depression state

3.3 Signal Datasets

For example, EEG provides neurological signals when studying brain correlates of mental health. Federated learning and EEG datasets can generate applications that read thoughts to decipher emotions, stress, and cognitive status [51–54]. Fig. 7 shows the emotion recognition processing using EEG signals.

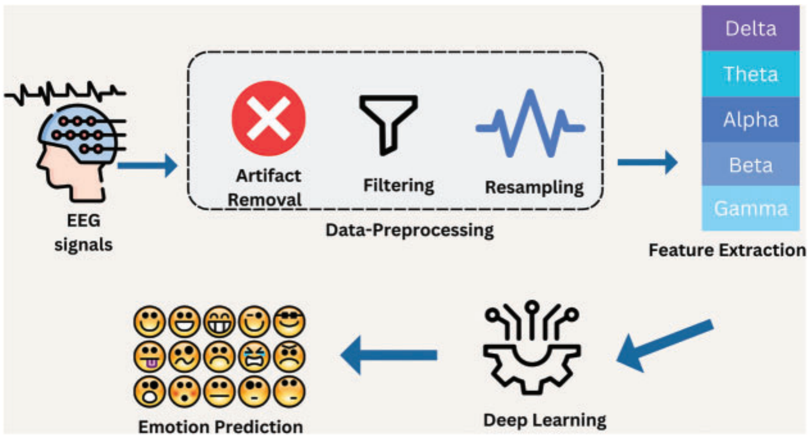

Figure 7: EEG processing based on deep learning models for emotion recognition

3.4 Image Datasets

Mood-related imagery and facial cues in the visual representation provide consequential perceptual context for interpreting mental health visually. Image derivate face signals and other visual cues are utilized in the normalizing models that analyze emotional well-being under federated learning applications [55–57]. Fig. 8 presents the image processing for predicting facial depression.

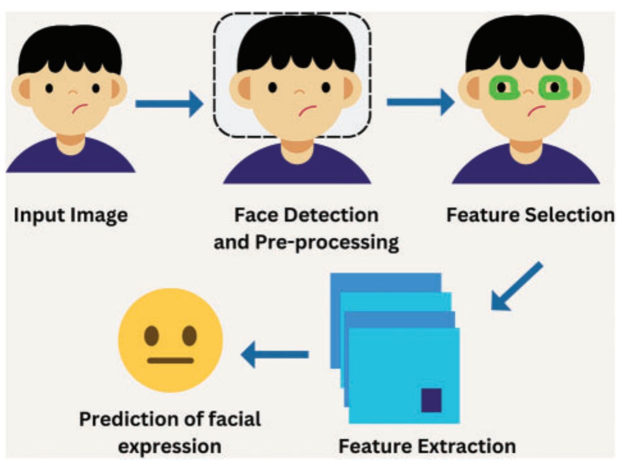

Figure 8: Image-based using machine learning models for predicting facial expression

3.5 Multimodal Datasets

Multimodal datasets include text, voice, signals, and performances, but a few result in rich mental health information. Federated learning applied to multimodal datasets incorporates a holistic approach that improves the accuracy and inclusiveness of mental health assessments utilizing data from multiple sources [40,58–60].

Applying multiple dataset types in Federated Learning-Based Mental Health Apps guarantees a multi-dimensional perception of people's mental health, which assists in creating efficient and personalized treatments. Fig. 9 shows the multimodal data processing.

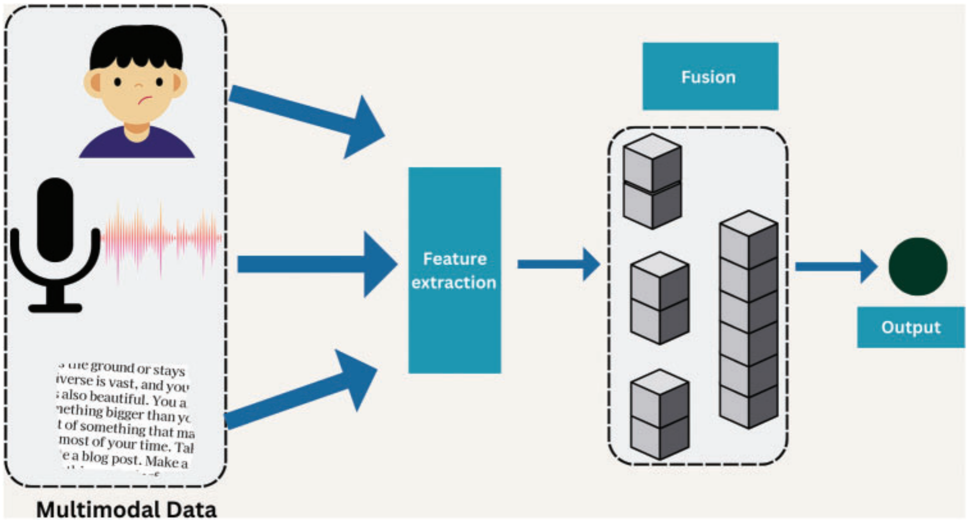

Figure 9: Multimodal data processing

3.6 The Frequently Used Datasets

Table 2 lists seven frequently used datasets by dataset type and task.

Table 2: The frequently used datasets in this research survey

Dataset name	Dataset type	Dataset task	Research
DAIC-WOZ dataset [61]	Speech	Depression detection	[47,48]
WESAD dataset [62]	Multimodal	Stress detection	[63]
DEAP dataset [64]	Signal	Stress detection, emotion detection	[52,65,66]
AMIGOS dataset [67]	Signal	Emotion recognition	[40]
DREAMER dataset [53]	Signal	Emotion recognition	[40]
IEMOCAP [68]	Speech	Emotion recognition	[50,69]
Affective Road database [70]	Physiological data	Driver Stress detection	[70]
FER-2013 [71]	Image	Emotion Recognition	[72,73]
RAVDESS [74]	Speech	Emotion Recognition	[75–77]
SEED [78]	EEG signal	Emotion Recognition	[52]

3.6.1 DAIC-WOZ Dataset

The DAIC-WOZ (Distress Analysis Interview Corpus) is a clinical interview database designed to facilitate the exploration of mental health issues, such as anxiety, depression, and PTSD.

3.6.2 WESAD Dataset

The WESAD (Wearable Stress and Affect Detection) dataset is a valuable resource for affect recognition, specifically focusing on wearable stress monitoring systems to enhance human-computer interaction. The dataset addresses the gap in the affective computing community by providing a publicly accessible, multimodal dataset of reliable data for affect detection and stress analysis.

WESAD includes motion and physiological data collected from both chest-worn and wrist-worn devices. It comprises body temperature measurements, electrodermal activity, electrocardiogram, electromyogram, respiration, and blood volume pulse.

This dataset goes beyond previous studies by combining three affective states, stress, neutral, and amusement, providing a better understanding of emotional states.

The dataset also incorporates self-reports from 15 subjects gathered through established questionnaires, enriching the dataset with subjective insights. A benchmark is established using essential features and standard machine learning methods to assess its utility.

3.6.3 DEAP Dataset

The DEAP dataset examines human emotional states and captures both neurophysiological and physiological signals. The dataset includes physiological signals and EEG recordings from 32 participants who viewed 40 one-minute-long segments of music videos. In order to improve the richness of the dataset, participants were asked to provide ratings for each video, assessing levels of dominance like/dislike, familiarity, valence, and arousal.

The dataset features frontal face recordings for 22 out of 32 subjects. This adds depth and context to facial expressions and provides an understanding of their link with the measured physiological signals while watching music videos.

The novel stimuli selection method is a combination of different approaches. The website includes video highlight detection, Last FM affective tags, and an online assessment tool to ensure diverse and emotionally engaging stimuli. This methodology aims to consider a great variety of affective responses using stimuli close to human life's realities.

This multimodal dataset provides a pivotal resource to researchers investigating music photography's human affective states under visual stimuli and music. The dataset available to researchers comprises, in addition to EEG data, peripheral physiological signals, subjective ratings, and facial expressions, thus adding to its usefulness in complex stimulus-physiology-subjective emotional experience interplay investigation.

3.6.4 AMIGOS Dataset

The presented database is a comprehensive resource for research on personality traits, affect, and mood, using signals related to neuro-physiology in a multimodal study. Unlike other databases, this collection elicits effects through long and short videos, integrating two configurations: individual groups of viewers and individuals. The primary objectives are to investigate individual affective responses about mood and personality and to analyze how these responses are influenced by the individual/group viewing configuration and video duration (short *vs.* long).

The databases were collected through two experiments involving 40 participants who watched short and long emotional videos alone or in groups. Neurophysiological signals, including ECG, GSR, and EEG, were captured using wearable sensors and full-body, frontal, and depth videos. Participants were also assessed for personality traits and mood using Positive and Negative Affect Schedules and the Big Five.

Emotions were annotated through external evaluation of arousal with valence and also self-assessment. The database supports analysis of correlations between these assessments and various factors, including video length, personality, mood, and social context. This allows for a detailed exploration of emotional responses in different scenarios.

3.6.5 DREAMER Dataset

DREAMER is a multimodal database for affect elicitation research featuring ECG and EEG signals recorded during audio-visual stimulus exposure from 23 participants. It includes self-assessment reports on valence, arousal, and dominance, using portable and cost-effective Emotiv EPOC and Shimmer2 sensors. The classification results for these affective states are comparable to those from databases using more expensive medical-grade equipment.

3.6.6 IEMOCAP Dataset

The IEMOCAP data release offers a rich dataset capturing affective interactions involving ten male and female actors. The database encompasses scripted and improvised sessions, totaling around 12 h of audio-visual content. Detailed information is provided for each recording, including audio and video of both participants, Motion Capture data of face, head, and hand movements for one interlocutor, text transcriptions of conversations, and word-level, phone-level, and syllable-level alignment. Additionally, annotations by multiple annotators offer categorical and dimensional labels for each utterance, enhancing the dataset's depth for emotion-related research.

3.6.7 Affective Road Dataset

In driver monitoring, physiological measures of arousal and stress are developed and validated using two groups of wireless sensors. These sensors collect data on heart rate, electrodermal activity, respiration, skin temperature, and hand movements, while a separate network tracks environmental parameters like temperature, humidity, pressure, and light. This approach integrates physiological responses with road environment data to assess driver well-being and performance.

This multimodal dataset can be a valuable resource for researchers in this field of study, which involves music, visual stuff, and human affective. With the addition of EEG, peripheral physiological signals, subjective ratings, and facial expressions, we expanded the utility of this dataset beyond using it to investigate direct associations between stimuli and subjective emotional experiences.

3.6.8 The FER2013 (Facial Expression Recognition 2013) Dataset

Consists of seven emotions of grayscale images: Angry, Disgust, Sad, Surprise, Fear, Happy, and Neutral. The dataset includes 28,709 examples in the training set, 3589 images in the public testing set, and 3589 images in the private test set.

3.6.9 RAVDESS Dataset

The RAVDESS includes 7356 files (24.8 GB) from 24 professional actors (12 female, 12 male) speaking two lexically-matched statements with a North American accent. It features speech expressing seven emotions and song expressing five emotions, each at two intensity levels plus a neutral expression. The dataset is available in three formats: audio-only (.wav), audio-video (.mp4), and video-only.

3.6.10 SEED Dataset

The SEED dataset was designed to explore emotional responses to film clips. Seventy-two clips were chosen to elicit emotions such as happiness, sadness, fear, and neutrality. Fifteen subjects participated in three sessions, each viewing 24 clips, with EEG signals recorded using a 62-channel ESI conducted by NeuroScan System and eye movements tracked by SMI eye-tracking glasses.

The collected data were processed to extract critical features. EEG signals were down-sampled to 200 Hz and filtered to reduce noise, with Power Spectral Density (PSD) and Differential Entropy (DE) features extracted across the delta, theta, alpha gamma, and beta frequency bands. Additionally, eye movement features such as pupil diameter, fixation duration, saccades, and blink events were extracted from the recordings.

4 Use Cases by Symptoms and Disease

The use cases of FL mental health applications answer to a specific medical condition or a set of symptoms, as shown in Fig. 10. This method is flexible and enables individualized support or interventions to be offered. The following are several famous use cases characterized by symptoms and conditions.

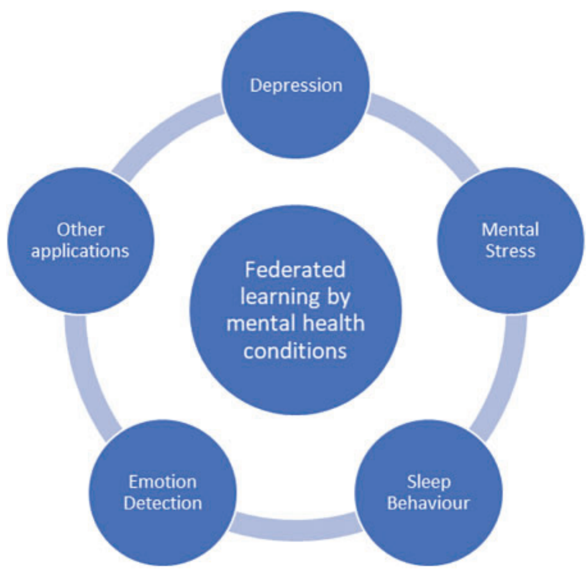

Figure 10: Federated learning by mental health symptoms

4.1 Depression

Federated Learning Programs for Early Detection of Depression and Depression in Relation to Eating Disorders can incorporate behavioral analysis, the provision of individualized therapeutic material, and the capacity to monitor mood.

In 2021, Liu et al. enhanced the depression treatment robot (DTbot), an intelligent robot for depression therapy, using federated learning and conventional deep learning techniques. They solved the problems of central server-based models by localizing patient data, which optimizes treatment efficiency and addresses privacy issues. This is a potentially helpful integration of technology into mental health care [79].

Similarly, Xu et al. in 2021 addressed the problem of diagnosing depression and argued that the latter entails extremely inconsistent manifestations. The traditional centralized machine learning methods faced difficulty aggregating patient data, which must be highly confidential. The research adopted federated learning with a multi-view approach to depression analysis in cross-institutional to address privacy issues. The approach incorporated later fusion techniques to address inconsistent time series data. Comparative experiments demonstrated that with enough participants, the Federated Learning Framework achieves a prediction accuracy of 85.13%, a 15% improvement over local training. Even with fewer participants and sufficient data, the accuracy remained high at 84.32%, showing a 9% enhancement [80].

In 2021, Pranto et al. introduced a model combining deep neural networks and federated learning for monitoring mental health through social networking datasets, particularly keyboard input. Utilizing RNN and federated learning, the system detects daily depression levels. The global model is located at a central server, and users' local devices test their keyboard data against it. Anonymized test results contribute to a global sentiment dictionary, which is updated daily. The model attained an accuracy of 93.46% on the 60th day, showing its effectiveness in continuously monitoring mental health through user-generated social media content [36].

In 2022, Bn et al. proposed FL for decentralized and privacy-preserving depression analysis in speech. Utilizing the DAIC-WOZ dataset, they demonstrated that federated models achieve a vital depression assessment with only a 4%–6% accuracy reduction compared to centralized approaches. These FL models perform better than previous methods, ensuring small memory footprints, energy efficiency, and short inference latency [48].

In 2022, Lemos et al. presented the Federated Artifcial Intelligence solution for moniToring mental Health status after cancer treatment (FAITH) study, which aims to remotely assess breast and lung cancer survivors in Spain and Portugal for signs of depression. They used markers such as nutrition, sleep, activity, and voice and employed standardized depression measures (Ham-D and HADS) for regular evaluations [81].

FAITH employs a smart band synced with a smartphone via the FAITH App to assess depression factors with minimal user input. The study aims to develop an FL Framework to predict depression while preserving data privacy. This model offers healthcare providers early alerts for timely mental health interventions, enhancing the quality of life for cancer survivors.

In 2022, Cui et al. examined the privacy concerns associated with centralized training depression diagnosis models based on speech. Utilizing FL, the study demonstrated for the first time that such models can be trained in a privacy-maintaining setting, maintaining decentralized speech data on users' devices. The proposed FL model, integrated with defenses like norm bounding and differential privacy, proves robust against attacks. Experiments using the DAIC-WOZ dataset indicated that the

FL model achieves great results comparable to centralized learning approaches, ensuring user privacy in speech data [47].

In 2022, Gupta et al. proposed an FL Framework using clustering to integrate multi-source data and improve standard machine learning models. It assesses the framework's performance against other cooperative learning methods, highlighting its potential to maintain patient privacy across institutions [82].

In 2023, Lee et al. conducted across five South Korean tertiary hospitals, developed a federated, differentially private model to predict bipolar disorder transitions in patients initially diagnosed with depression. Utilizing data from 17,631 patients for model development and 4541 patients for external validation, the federated model outperformed local models with AUCs of 0.726 and 0.719, respectively. Key predictors included the Charlson index, severe depression, anxiolytics, young age, and visiting months, with bipolar transitions linked to seasonality, especially in spring and summer. This study indicated federated learning's effectiveness in creating predictive models while preserving patient privacy [83].

In 2024, Khalil et al. explored FL for detecting depression in multilingual contexts from English, Arabic, Russian, Spanish, and Korean datasets. FL performed similarly to centralized and local models in IID scenarios but faced challenges in non-IID settings due to data disparities. Despite these challenges, FL holds promise as a privacy-protecting approach for mental health diagnostics [43].

In 2024, Liu addressed privacy concerns using social media data for depression detection by proposing a federated deep learning framework. This framework analyzed data from three social media platforms while preserving privacy and supporting clinical decision-making with accurate depression risk identification and intervention strategies. Experimental results indicated that the approach achieves state-of-the-art performance, offering a dynamic and effective clinical decision support system for personalized treatment [35].

In 2024, Gupta et al. focused on developing a privacy-preserving system for identifying Major Depressive Disorder (MDD) using EEG data through FL. FL allows for secure training of deep learning models without compromising patient privacy. The research evaluated various deep learning algorithms, including LSTM, GRU, Bi-LSTM, and 1D-CNN, for 3-channel EEG-based MDD screening using the MODMA dataset. Results showed that FL effectively trains models in a privacy-preserving way, with the potential for future research to expand and enhance MDD diagnosis methods [84].

Table 3 shows that most works on depression detection tasks implemented federated deep learning. The study highlights the detection of depression and its fine-grained level as well. The dataset came from several sources, including social networking data, mobile applications, standard datasets like DAIC-WOZ, and electronic health records.

Table 3: The previous studies of federated learning in depression identification

Authors	Methods	Dataset details	Task
Liu et al. (2021) [79]	Federated deep learning with CNN	–	Robot for depression treatment

(Continued)

Table 3 (continued)

Authors	Methods	Dataset details	Task
Xu et al. (2021) [80]	Federated deep learning based on GRU	The data utilized in the experiment is sourced from an observational study conducted using a freely available mobile application called BiAffect	Depression analysis
Pranto et al. (2021) [36]	Federated deep learning based on RNN	Social networking dataset	Depression level detection
Bn et al. (2022) [48]	Federated deep learning based on ResNet	DAIC-WOZ dataset	Depression severity classification
Lemos et al. (2022) [81]	The hamilton depression rating scale	Electronic health records	Severity of depressive symptoms
Cui et al. (2022) [47]	FL in speech	DAIC-WOZ dataset	Depression detection
Gupta et al. (2022) [82]	FL on CNN	HRV dataset	Depression detection
Lee et al. (2023) [83]	Federated deep learning based on deep & cross network	Electronic health records	Predicting bipolar transition in patients with depression
Khalil et al. (2024) [43]	Federated learning for detecting depression using multilingual language models	Multilingual textual data	Depression
Liu (2024) [35]	Federated deep learning	Social media data	Depression
Gupta et al. (2024) [84]	Federated deep learning	EEG data	Depression

4.2 Mental Stress

Federated learning applications designed for stress management utilize user data, including physiological signals, to create personalized interventions. These interventions may include real-time stress detection and adaptive coping strategies.

Another study relevant to this research is that of Vyas and Das, which deals with predicting driver stress and behavior for ADAS, which is essential in enhancing driving safety. The study estimates driver stress and driving behavior changes based on an analysis of historical trip data. This study uses LSTM with FCNN to predict driver stress levels. It also connects with driving behavior and stress and presents an intelligent recommendation system for taxi firms to propose appropriate drivers for future trips [85].

In addition, the proposed approach integrated FL in the Vehicular Edge Computing study. As a result, roadside units are integrated to do all data computations remotely. Testing the model on the UAH-DriveSet dataset demonstrated that this system can predict stress with 95% accuracy. The results showed that the model effectively enhances driving quality and the overall driving experience, suggesting that similar systems could improve road safety.

In 2021, Liu et al. evaluated the FL of the mHealth model, simulating affective state prediction using data from a chest-worn device. The FL model reached an accuracy of 92.8% in classifying neutral, stress-inducing, and amusement tasks, outperforming individual models that achieved 90.2%. These highlights federated learning's potential in mHealth for secure, high-performance predictions [17].

In 2022, Fauzi et al. deployed an FL-based stress detection system and compared the individual, centralized, and FL methodologies using the WESAD dataset with LR as their classifier. This result showed that federated learning is less accurate when compared to both individual and centralized learning. This was followed by the average F1-measure for the individual learning paradigm, which was 99.96% and an accuracy of 99.98%. The lower accuracy shown in Federated Learning highlights the potential privacy-preservation *vs.* model performance trade-offs that will be of interest when applying stress detection systems into individual-data-privacy first scenarios [63].

In 2022, Rafi et al. monitored the Internal State of Drivers Towards Enhancing Riding Comfort for Car Occupants: Foundations and Development of Control Law for ADAS. The proposed driver's stress monitoring system was based on physiological signals analysis to detect stressful conditions automatically. The system employed new-in-training about the individual differences among drivers [86].

The Federated Learning approach uses a personalization training regime that prioritizes samples from drivers with close posts like the target driver, hence customizing the prediction model according to every driver's specific personality. This strategy is better than the conventional paradigms, which are optimized for average performance for all the users in each dataset. The AffectiveROAD public database study demonstrated the effectiveness of this personalization approach in improving stress estimation performance. Such results demonstrate the prospective of federated learning in driver stress monitoring, a more personalized and efficient approach in contrast to the traditional approaches [70].

A personalized, federated learning algorithm for stress-level classification was proposed by Jiang et al. In 2023. They demonstrated accuracy improvement by over 7% and 12%, respectively, compared to two recently introduced baseline algorithms under the proposed approach. Also, the two baseline algorithms realized a significant decrease of 37.5% and 9.6% in training time. They introduced a novel cold-start algorithm designed for integrating new clients into the trained system, achieving robust performance in individual classification accuracy and overall training time [87].

Federated Deep Learning Based Wearable Electrodermal Activity for Preserving Chronic Aging Patient Data Privacy. The research utilizes the WESAD dataset, encompassing five data categories: distraction, distress, and meditation experience. Pre-processing transforms the raw dataset with SMOTE and min-max normalization. The FL-based approach trains their DNN model independently on the dataset when two users forward updates to the model. Each client analyses the results three times to overcome the problem of overfitting [88].

Experimental results indicated that when the FL-based DNN model is used, it delivers 86.82% accuracy and ensures patient data privacy. This approach outperforms prior studies in detection accuracy, underscoring the potential of FL-based DNN models for enhancing advanced stress classification from wearable data while preserving vital patient data privacy.

In 2021, Can et al. used FL to analyze the heart activity data collected from the smart bands and monitor the stress levels during different events. The federated learning application showed promising results exhibiting the relevance of wearable IoT-based biomedical monitoring devices. The method maintained the secrecy of the extracted information, demonstrating the efficiency of federated learning in this domain [89].

In 2023, Vyas et al. developed FedSafe as a driver stress-oriented recommendation system using FL to improve driving experience and wider transportation system benefits. FedSafe uses vehicle telematics and physiological data to explore stressed conditions and driving habits, providing personalized advice for the next trip to minimize on-road stress and secure trips. Collaborative learning using vehicle data without transferring raw information among drivers, thus increasing transmission data overhead, is made possible through incorporating Federated Learning. Such a method is also appropriate for the vehicular network whose popularity requires edge computation [90].

An extensive human-in-the-loop study using publicly available natural driving datasets (UAH DriveSet, HCI Lab, PhysioNet) demonstrated that the proposed FedSafe system shows impressive predictive capabilities. It achieved 97% accuracy in predicting driver stress and 98% in identifying driving behavior, measured by AUC and F-measure. The Federated Learning approach substantially reduces transmission overhead by approximately 25 times, indicating the efficiency and effectiveness of FedSafe in stress monitoring and behavior recognition for enhanced road safety and driving experiences.

In 2024, Alahmadi et al. explored using the Internet of Medical Things for remote patient monitoring and data-driven diagnosis. They presented use cases and recent developments in FL-based IoMT data analysis, particularly in mental stress detection. The proposed framework demonstrated that FL can significantly reduce communication overhead for local devices, from 10.02 MB/day to as little as 754 B/day, compared to traditional non-FL methods. This reduction enhances the efficiency and practicality of using FL in IoMT for continuous health monitoring (39).

Table 4 summarizes all the federated learning in stress identification tasks, indicating that federated deep learning is prevalent in these tasks. In addition, the dataset involves driver stress data sets such as the AffectiveROAD dataset and the UAH-DriveSet dataset. The standard dataset, such as the WESAD dataset, collected the signals from chest wear and wristbands and integrated them into these tasks. The dataset was gathered from several sources, including social networking data, mobile applications, standard datasets like DAIC-WOZ, and electronic health records.

Table 4: The literature survey for federated learning with stress recognition

Authors	Methods	Dataset details	Task
Vyas et al. (2020) [85]	Federated deep learning with LSTM and a fully convolutional network	Driver stress levels.	Predicting driver stress and behavior
Liu et al. (2021) [17]	Federated deep learning with neural networks	Motion and physiological data were gathered from a chest-worn device	Predicting the affective state such as a neutral, stressful task or amusing
Fauzi et al. (2022) [63]	Federated machine learning with logistic regression	WESAD dataset	Stress detection

(Continued)

Table 4 (continued)

Authors	Methods	Dataset details	Task
Rafi et al. (2022) [86]	Federated machine learning with support vector machine	AffectiveROAD database contains physiological data from 13 drivers	Monitoring driver stress
Jiang et al. (2023) [87]	Federated deep learning based on convolutional layer	WESAD dataset	Stress identification
Almadhor et al. (2023) [88]	Federated deep learning	WESAD dataset	Stress identification
Can et al. (2021) [89]	Federated deep learning	Data gathered from smart bands	Monitor stress levels
Vyas et al. (2023) [90]	Federated deep learning	The UAH-DriveSet dataset	Driver stress monitoring
Alahmadi et al. (2024) [39]	Federated reinforcement learning	WESAD dataset	Mental stress detection

4.3 Sleep Behavior

Federated learning contributes to applications targeting sleep-related issues by analyzing data from wearables and devices. These apps provide insights into sleep patterns, identify factors affecting sleep quality, and offer personalized recommendations for improved sleep hygiene.

In 2022, Khao et al. applied ML to analyze and predict sleep quality. They took things further by introducing FL into the analysis. The research used an ML model, FedMCRNN, incorporating multi-modal data collected from wearable sensors of sleep quality prediction. In the many-to-one setting, accuracy was 96.774%. In the many-to-many setting, accuracy was 68.721%. Federated learning using multiple convolutional recurrent neural networks (FedMCRNN) outperforms traditional ML models and prevails over other advanced methods for sleep quality prediction. This is important for sleep analysis, and FL can also support doctors using AI, demonstrating that it can increase predictive accuracy and feature understanding [91].

In 2022, Yin et al. investigated EEG data for sleep staging and proposed FL as a solution. They employed the K-means partitioning algorithm to convert EEG datasets into non-independent and identically distributed unbalanced datasets simulating various user datasets. MLP networks were used for the analysis, and the research examined privacy leakage problems in Florida. The user's EEG data was protected using DP. The research indicated that errors are related to the disparity in client-based data distribution between L and CL [51].

In 2023, Anido-Alonso et al. proposed several strategies for deep learning networks to achieve inter-database generalization while ensuring patient data privacy during automatic sleep staging. Implementing the sub-sampled federated stochastic gradient descent (ssFedSGD) algorithm with four ensemble strategies, the decentralized learning approaches outperformed baseline local methods and matched the generalization results of centralized approaches. The findings showed that decentralized methods provide advantages in flexibility, scalability, and data privacy [92].

In 2024, Ma et al. addressed the challenge of limited labeled data in automatic sleep staging by proposing an FL strategy for secure collaboration among institutions. The Federated Semi-Supervised Sleep Staging method enhances labeled data and task knowledge by integrating external knowledge from other institutions using single-channel EEG data. It incorporates local and global relationships, employs pseudo-labeling optimization for reliable pseudo-labels, and uses prototype-contrastive learning to clarify relationships. Experimental results showed that this method outperforms comparative approaches on two publicly available datasets [93].

In 2024, Borges et al. explored FL for sleep detection in human-in-the-loop Cyber-Physical Systems, addressing privacy concerns with sensitive user data. FL achieved over 84% accuracy, comparable to traditional machine learning models. The research emphasized the importance of managing human error inputs, demonstrating FL's potential as a privacy-preserving and accurate solution for sleep detection [94].

In 2024, Dautov et al. studied developing an FL system for drowsiness detection using non-IID data. They compared the performance of this federated setup with a traditional centralized approach. The results identified that the centralized model achieved approximately 83% accuracy and recall precision, while the federated model's best performance reached around 66%, with an average performance of about 50% [95].

Table 5 presents previous literature on federated learning in sleep behavior. It indicates that federated deep learning is often and primarily employed to monitor sleep behavior using EEG data, a brain signal.

Table 5: Previous studies of federated learning in sleep behavior

Authors	Methods	Dataset details	Task
Khao et al. (2022) [91]	Federated deep learning with CNN	Data from multiple modalities were obtained through wearable devices	Predict sleep quality
Yin et al. (2022) [51]	Federated deep learning with multilayer perceptron	EEG data	Monitoring sleep staging
Anido-Alonso et al. (2023) [92]	Federated deep learning with CNN and LSTM	Sleep staging databases, including DREAMS, Dublin, SHHS, Telemetry, ISRUC, and HMC datasets, were employed	Monitoring sleep staging
Ma et al. (2024) [93]	Federated semi-supervised learning	EEG data	Monitoring sleep staging
Borges et al. (2024) [94]	Federated deep learning	ISABELA dataset	Sleep detection
Dautov et al. (2024) [95]	Federated deep learning based on CNN	Driver drowsiness dataset	Drowsiness detection

4.4 Emotion Detection (Most of the Work Presented)

Federated learning allows applications to detect mood variations, identify triggers, and provide timely solutions for people suffering from mood disorders [96]. These interventions can be anything from activities that improve mood to putting consumers in touch with mental health specialists.

In 2020, Chhikara et al. integrated speech signals and facial expressions to identify micro expressions and generate an emotion feature, providing insights into users' mental health. Utilizing federated learning, the proposed scheme allows clients to train the model locally without breaking privacy. Instead of sending raw data to a central server, only model weights are transmitted, creating a more robust global model that is sent back to users. This approach ensures inter-organizational training without violating privacy, leading to good results. The collected user data is monitored to analyze mental health, offering counseling solutions during challenging times [56].

In 2020, Latif et al. applied SER applications with federated learning, which allows collaborative learning without sharing raw speech data. The study achieved good results compared to novel methods by evaluating this approach using the IEMOCAP dataset. The dataset included four basic emotions (angry, neutral, happy, and sad) from the IEMOCAP corpus, and the proposed system employed CNN and RNN architectures for emotion classification. The LSTM-based classifier slightly outperforms CNNs [69].

In 2022, Nandi et al. assessed the interconnectedness of emotional and physical health, emphasizing the significance of simultaneous care for both aspects. It explored affective computing, focusing on detecting emotional states through physiological measurements such as electrodermal activity data (EDA), respiratory belts (RB), and EEG. Focusing on real-time multi-modal emotion state recognition from wearable sensors emerges as a prominent topic. The challenge lies in processing high data generation rates and ensuring data privacy, particularly in decentralized settings [65].

In order to address these challenges, the study introduces Fed-ReMECS, a federated learning framework established for the real-time detection of emotion states within multimodal physiological data streams obtained from wearable sensors. This structure works well and allows it to construct a global classifier without touching users' local data, causing privacy issues in the IoT environment. The proposed algorithm, Fed-ReMECS, can protect users' privacy while maintaining efficiency and scalability, as demonstrated through experimental studies conducted with the DEAP dataset. The results show that it can be employed to develop robust and privacy-protecting emotion classification systems for real-time usage in IoT [65].

In 2022, Singh et al. introduced an FL Approach designed to classify emotions into seven categories: happiness, excitement, anger, empathy, horror, nervousness, and astonishment. The priority is privacy when it comes to the proposed framework because, although it can classify data with accuracy like the conventional centralized machine learning solution, it does it in a confidential manner whereby individual data is not exposed [97].

In 2022, Xu et al. proposed an extension of Federated Learning to address the problem of scarce data available for training emotion detection models based on electroencephalogram signals. With FL, several clients' cooperation is possible without disclosing information and, thus, privacy concerns. The proposed framework achieved a high accuracy of 90.74% in emotion recognition on the SEED and DEAP datasets. When applied to DEAP dataset clients, the FL method outperformed local training by 29.31%, emphasizing the necessity of FL for emotion recognition tasks. In addition, the study highlighted non-IID data on FL training, demonstrating a 14.89% decrease in accuracy compared to IID data [52].

In 2022, Salman et al. implemented FER on small smart devices due to computational constraints. They proposed a real-time image- and video-based facial expression recognition model that overcomes these limitations. The approach involved personalization through fine-tuning a central model with unlabelled videos from the target subject using an FL strategy. The image facial expression recognition model generated pseudo-labels, and adaptation was performed by averaging local model weights. Results demonstrated that this method improves edge device and central video facial expression recognition model performance, achieving a 13.1% gain in F1-scores for personalized models and up to a 3.4% improvement in the central video facial expression recognition model's mean micro F1-score. The lightweight solution is well-suited for deployment on small smart devices [57].

In 2022, Zhang et al. implemented facial expression cognition technology, emphasizing the privacy concerns in current distributed machine learning for face monitoring data. The proposed solution introduces an FL framework for unsupervised face recognition post-exercise. Employing a graph AE design, the framework enables collaboration among multiple edge devices to optimize a common objective function, enhancing global model efficiency. A multidomain learning loss function promotes shared feature representation across tasks, bolstering domain adaptability. Adversarial learning further improves recognition within each domain. Experimental validation on diverse multidomain expression datasets demonstrated a 19% increase in F1-score compared to the benchmark approach [98].

In 2023, Chen proposed an online teaching emotion recognition system with federated learning for assessing AI-assisted teachers' teaching effectiveness. Although the current focus in intelligent education centers on enhancing students' learning efficiency, this proposal emphasizes the importance of evaluating teachers' educational impact. The Federated Learning approach ensures the security, privacy, and legal compliance of teachers' data while enabling collaborative training and joint modeling. By recognizing teachers' teaching emotions, the system aids in analyzing teaching levels, identifying issues in online teaching processes, and enhancing overall teaching proficiency. Experimental results demonstrate the model's effectiveness in recognizing facial emotions during online education, especially in scenarios with independent and unbalanced data among participants [99].

In 2023, Agarwal et al. raised privacy concerns in emotion recognition from physiological signals by proposing a Federated Learning Framework. Unlike centralized datasets, this decentralized approach preserves privacy, essential for sensitive data such as EEG recordings. The convolutional neural network model directly processed EEG signals to extract features from the DEAP dataset. The proposed architecture achieved accuracy scores of 72.22%, 70.10%, and 66.99% for dominance, arousal, and valence, respectively, by maintaining the non-IID nature of the data. The study discussed trade-offs between performance and privacy in Federated Learning [66].

In 2023, Zhang et al. introduced FedAudio, designed to address the lack of audio data and tasks in existing FL benchmarks. With the increasing concern for data privacy on consumer devices, FedAudio aims to facilitate research in Florida for audio-related tasks. The benchmark includes four representative audio datasets, spanning three essential audio tasks relevant to FL use cases. A specific feature of FedAudio is the incorporation of data noises and label errors into the datasets, simulating challenges encountered in real-world FL system deployments. The benchmark provides results that enable researchers to compare algorithms effectively. FedAudio is anticipated to inspire and advance FL research in audio tasks, benefiting the speech research community. Access to datasets and benchmark results is available [50].

In 2024, Gahlan et al. introduced a Federated Learning (FL) approach based on the Multi-modal Emotion Recognition System (F-MERS) designed for assessing complex emotions using EEG, ECG, GSR, and respiratory therapy (RESP) physiological sensor data. In contrast to traditional machine learning classifiers that risk privacy violations, F-MERS employs FL, allowing local model updates without exposing raw training data. Utilizing MLP as the base model, F-MERS achieved accuracies of 87.90%, 89.02%, and 79.02% on the DEAP, AMIGOS, and DREAMER datasets, respectively. The study explored scalability, efficient communication, and privacy preservation compared to a non-FL MLP baseline model. With multi-modal physiological sensors, this represents the first FL-enabled framework for detecting complex emotions in three dimensions (valence, arousal, and dominance) [40].

Table 6 illustrates that most emotion tasks using federated deep learning and emotion datasets have various forms, such as speech and facial expression. Combining both data types helps to make more robust models for emotion recognition. DEAP datasets containing EEG, peripheral physiological, and audio-visual recordings are primarily employed in federated learning tasks.

Table 6: The literature surveys of emotion detection

Authors	Methods	Dataset details	Task
Chhikara et al. (2020) [56]	Federated deep learning of CNN and support vector machine (SVM)	The FER2013 dataset is commonly utilised for facial emotion recognition, while RAVDESS dataset is employed for speech emotion recognition	Emotion detection using speech recognition
Latif et al. (2020) [69]	Federated deep learning on convolutional encoder network and Bidirectional LSTM	IEMOCAP, EMODB, and MSPIMPROV dataset	Speech emotion recognition
Nandi et al. (2022) [65]	Federated deep learning with feed-forward neural network)	DEAP dataset	Emotion state detection
Singh et al. (2022) [97]	Federated learning	–	Seven categories: amusement, adoration, disgust, empathic pain, fear, anxiety and surprise
Xu et al. (2022) [52]	Federated deep learning based on CNN	DEAP and SEED datasets	Emotion recognition
Salman et al. (2022) [57]	Federated deep learning based on CNN	Facial expression dataset AffectNet, CREMA-D, and MSPIMPROV datasets	Emotion recognition

(Continued)

Table 6 (continued)

Authors	Methods	Dataset details	Task
Zhang et al. (2022) [98]	FL framework for unsupervised face recognition employing a graph AE design	Facial expression	Emotion recognition
Chen (2023) [99]	Federated learning for online teaching emotion recognition detection	–	Emotion recognition
Agarwal et al. (2023) [66]	Federated deep learning based on CNN	DEAP dataset	Emotion state detection
Zhang et al. (2023) [50]	Federated deep learning with two convolution layers and one GRU	Four audio datasets such as Google Speech Commands, IEMOCAP, CREMA-D, Urban Sound	Emotion recognition
Gahlan et al. (2024) [40]	Federated deep learning based on MLP	DEAP, AMIGOS, and DREAMER dataset	Emotion state detection

4.5 Other Applications

Other mental health applications use federated learning to address mental health concerns such as loneliness detection and mental health symptom detection.

In 2022, Qirtas et al. highlighted loneliness among college students needing improved technology-based detection methods considering individual behavioral differences. The research proposed loneliness detection, utilizing passive sensing data from mobile phones to capture rich user behavioral information. Employing unsupervised clustering, the study identified small groups of students with similar behavioral patterns, allowing for the understanding and detection of loneliness. By creating group-specific classification models, the research demonstrates an improvement in accuracy over generalized models. The findings underscored personalized approaches in mental health interventions and highlighted the value of passive sensing data for creating tailored loneliness detection approaches [100].

In 2022, Ahmed et al. addressed the need for diverse patient data in training DNNs for mental health symptom detection, introducing a structural hypergraph with an emotional lexicon and a federated learning-based embedding model. The model used consecutive word sequences and attention-based mechanisms to enhance semantic word representations, incorporating grammatical, vocabulary, and dynamic lexicon analysis. Experimental results showed that using a Bi-LSTM architecture with an attention mechanism, the approach achieved a region of convergence (ROC) of 0.86, demonstrating its effectiveness in encoding emotional words and improving clinical applicability [101].

In 2024, Sahu et al. explored federated learning for private and accurate AI-based schizophrenia diagnoses using distributed datasets while preserving individual privacy. Advanced AI algorithms were applied to diagnose schizophrenia, demonstrating federated learning's potential as a secure and effective method for mental health diagnostics. The study highlighted federated learning's ability to enhance diagnostics while maintaining data confidentiality [102].

In 2024, Aversa et al. explored using FL to enhance technologies for monitoring, diagnosing, and managing specific health conditions while prioritizing privacy, confidentiality, and cybersecurity. The project aims to address the current lack of privacy-respecting solutions in the market. REDRAW focused on studying and refining dynamic cloud-edge deployment techniques that utilize FL models across three real-world contexts. The goal was to improve existing technological solutions while adhering to the strategic and non-functional constraints prevalent in the Italian and European healthcare landscapes [103].

With a focus on other mental health applications, the work also highlighted areas such as wellness detection, loneliness detection, and other mental disorders like schizophrenia. The methods employed range from federated unsupervised learning to federated deep learning. The primary concern with using federated learning in this context was to protect the privacy of mental health data.

5 Backgrounds for Federated Learning

The main techniques used in the research regarding federated mental health learning are Federated Machine Learning and Federated Deep Learning.

5.1 Federated Machine Learning

FL revolutionizes the conventional model training landscape by decentralizing the process across multiple devices or servers, each holding local data samples. The primary reason is to safeguard privacy and security, especially where sensitive data such as financial and personal details are concerned. This approach allows collaborative training over various devices without exposing raw data—a giant step towards protecting user privacy [104–106].

Federated learning is one of the models with its core decentralized training. Instead of relying on a centralized server, FL implements the training phase on individual devices or servers in a decentralized manner. The data being raw is localized to maintain privacy as the first objective. Information disclosure risks are reduced as only model updates or aggregated information is shared [107,108].

One critical factor is collaborative learning, where several people participate and improve the model using the data specific to each participant, which enhances collaboration and increases knowledge among the participants [85]; a machine learning model for global training. Consolidating each participant's update develops a global model with aggregated knowledge that does not disclose specific individual data. The adaptability of federated learning for heterogeneous environments and its efficient communication and collaborative structure positions it as a potent paradigm for emotion recognition [109].

Fig. 11 focuses on the association between the local devices and the global server. There is an in-depth explanation of how this exchange is conducted as follows:

- **Local Model Training**

Each local device or server possesses its dataset, typically representing a user's data or a subset of users. The local model on each device is initially trained on its respective dataset. This training process utilizes the local data to update the model's parameters [110].

- **Model Updates**

Rather than transmitting raw data to a central server, which could break user privacy, only the updates to the local model are transmitted. The local device calculates the variance between the existing and refined model parameters post-training. These updates, often as gradients or weights, encapsulate the knowledge gained during local [111].

- **Secure Transmission**

These model updates are then transferred to the global server securely. Common cryptographic techniques, such as encryption, are employed to ensure the confidentiality of the exchanged information. Using secure transmission protocols prevents unauthorized access to the model updates during their process from local devices to the global server [104,112,113].

- **Aggregation at the Global Server**

Upon receiving updates from multiple local devices, the global server combines these updates to create a comprehensive global model. Aggregation methods vary but commonly involve averaging the model parameters across devices. This process captures the collective knowledge from all participating devices without exposing individual data [114].

- **Global Model Distribution**

The combined global model is then sent back to the local device. This generates a model that contains these globally applicable insights. In this regard, the local devices synchronize their models with the received global model, so every device enjoys collaborative knowledge without raw data exchange. Compared to the centralized model training that involves sending out sensitive information via many devices, Federated learning reduces the amount of data transmitted as it does not send all information on the models but sends model updates, which are later summed up at the global server, hence protecting the privacy [107].

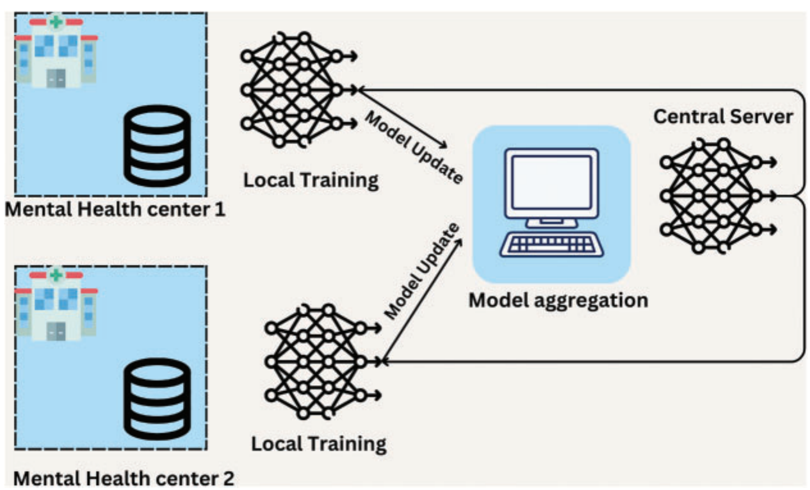

Figure 11: The link between local nodes and a central server

In the federated learning process, each of the K clients possesses its local dataset (Dk) without sharing it externally. The objective is to minimize a global loss function $L(w)$ in a distributed manner. This global loss function represents the model's overall performance across all clients. The loss function

(L_k) for the k-th client is defined as the average loss over its local dataset (Dk) in Eq. (1):

$$L_k = \frac{1}{n_k} \sum_{i \in Dk} l_i(W) \tag{1}$$

where w is the global model parameters, $l_i(W)$ is the loss function for a specific data sample i in the local dataset Dk, and n_k is the size of the local dataset for the k-th client.

The global goal of federated learning is to minimize the weighted average of these local client loss functions as Eq. (2), where the weights are proportional to the size of each client's dataset (n_k). The weighted average is calculated over all K clients in Eq. (2):

$$minL\,(W) = min \sum_{k=1}^{k} \frac{n_k}{n} L_{k(W)} \tag{2}$$

The total data sample size for all clients = n. The optimization process, in which all the clients take part in minimizing the global loss function, highlights the collaborative essence of federated learning. This approach ensures that the model is trained using data sets of different types without disclosing information about personal clients. Algorithms 1, 2 depict a federated learning process, highlighting its distributed and collaborative characteristics [115].

Algorithm 1: Federated averaging for global model updates.

Data: Client datasets $\{D_1, D_2, \ldots\ D_k\}$
Result: Global model parameters w
Initialization: Initialization global model parameter w';
While not converged do
  for each client k $\in\{1, 2, \ldots, K\}$ **do**
    Compute local model update Δw_k using local dataset D_k:

$$\Delta w_k = \arg\ min_{\Delta w} \frac{1}{n_k} \sum\nolimits_{i \in Dk} L_i(w + \Delta w)$$

  ;
  end
  Aggregate local model updates on the server;

$$\mathbf{w_{new}} = \frac{\sum_{k=1}^{K} \boldsymbol{n_k} * \boldsymbol{w_k}}{\sum_{k=1}^{K} \boldsymbol{n_k}}$$

  ;
  Distribute updated global model parameters $\mathbf{w_{new}}$ to all clients;
end
Global Model Optimization: optimize the final global model parameters;

$$w^* = \arg\ min_w \sum\nolimits_{i \in \bigcup_{k=1}^{K} Dk} L_i(w)$$

  ;

Algorithm 2: Federated averaging for local model updates.

Data: Global model parameters W, Learning rate η, Number of clients K
Result: Updated global modal parameters W
1. Initialize W randomly;
2. **for** global_epoch = 1 to max_global_epochs **do**
3.   **for** k=1 **to** K **do**

(Continued)

Algorithm 2 (continued)

4. Receive global model parameters W from a central server;
5. Receive local dataset D_k and its size $n_{k;}$
6. Compute local loss using L_k (W) using Eq. (1);
7. Computer local gradients ∇L_k (W);
8. Update local model: W_k '= W$-\eta. * \nabla$ L_k (W);
9. Send W_k 'to a central server;
10. **Central Server Aggregation;**
11. Aggregate local model updates: W' $= \frac{1}{K} \sum_{k=1}^{K} W_k{}'$;
12. Update global model: W = W$-\eta. * \nabla$ L (W');
13. **Broadcast** updated global model W to all clients;

5.2 Federated Deep Learning

Federated deep learning is a class of federated learning techniques that incorporates the features of deep neural networks. This is especially important in deep learning, where complex models are usually used. Unlike centralizing the training process on one server, federated deep learning distributes it across several servers and/or devices, each with its sample of locally available data. One of its primary objectives, aligning with Federated Learning principles, is to address privacy concerns. It achieves this by ensuring raw data is on local devices, with aggregated information or only model updates being shared to prevent the exposure of sensitive information [116,117].

The collaborative nature of federated deep learning involves participants contributing to global deep neural network training. Each participant refines the model using its local dataset, and these refinements are aggregated to construct an enhanced global model. Efficiency in communication is a hallmark of federated deep learning, focusing on minimizing the exchange of information between devices [118,119]. This approach is valuable in scenarios where communication resources are limited. Federated deep learning is designed to adapt seamlessly to heterogeneous environments, accommodating devices with differing data distributions. It scales effectively for large models, which are common in tasks, for example, speech recognition, image recognition, or natural language processing [120–123]. Federated deep learning aspires to create robust and generalized models that perform effectively across various scenarios by learning from diverse datasets across participants [124–126].

5.3 Software Packages for Federated Learning

A combination of general-purpose ML and DL libraries and specialized federated learning frameworks is often used for Federated Learning. The following is an overview of the software packages and tools commonly involved:

5.3.1 Machine Learning and Deep Learning Models

- **Scikit-learn:** Used for traditional machine learning models and evaluation metrics. It is commonly used for tasks such as preprocessing, model selection, and performance evaluation in federated learning [40,101].

- **Karas:** A high-level neural networks application programming interface (API), often used with TensorFlow as a backend for building and training deep learning models [65].

- **TensorFlow:** A comprehensive open-source library for machine learning and deep learning. TensorFlow Federated (TFF) is an extension for implementing Federated Learning using TensorFlow models [48,65,94,101].

5.3.2 Federated Learning Frameworks

- **TensorFlow Federated:** An open-source framework for federated learning that trains machine learning models across decentralized data sources while ensuring privacy. It is integrated with TensorFlow to use deep learning models in federated settings [22,40].

- **Flower:** [127] A flexible framework for federated learning that supports different machine learning and deep learning libraries, including TensorFlow and PyTorch. It is designed to be easy to use and integrates well with existing machine learning workflows [43,83,84,94,100].

- **PySyft:** [128] developed by OpenMined, is a Python library designed to facilitate the implementation of training algorithms with privacy mechanisms. It supports PyTorch and TensorFlow and offers features like secure multi-party computation and differential privacy (22).

5.3.3 Voice-Related Tasks

- **Librosa:** A Python package for analyzing and processing audio signals. It is often employed for extracting features like Mel-frequency cepstral coefficients (MFCCs), used in voice-related federated learning tasks [56].

5.3.4 Text-Related Tasks

- **Hugging Face Transformers:** A library for natural language processing tasks that provides pre-trained models for text classification, sentiment analysis, and text generation. It is often used in federated learning for text-related tasks [43].

5.3.5 Image-Related Tasks

- **OpenCV:** A library of programming functions mainly aimed at real-time computer vision. It is commonly used for image preprocessing in federated learning [129].

These packages allow federated learning across various data modalities, ensuring that machine learning and deep learning models can be applied to a range of tasks while leveraging the benefits of federated learning.

5.4 Performance Metrics of Federated Machine Learning and Deep Learning

Accuracy Metrics

Accuracy measures the proportion of correctly predicted instances, while precision and recall provide insights into positive predictions and identify relevant instances. The F1-score balances precision and recall, and the AUC-ROC curve evaluates the model's ability to distinguish between classes, reflecting its overall discriminative power [130,131].

Loss Metrics

Regarding federated learning, loss functions are critical in evaluating how well a model's predictions align with the actual values. Common loss functions include Cross-Entropy Loss for classification tasks and Mean Squared Error for regression tasks. In a federated context, calculating the average loss across all participating clients can provide a clear picture of the model's performance and effectiveness in learning from distributed data sources [132].

Communication Efficiency

Communication efficiency is crucial in federated learning, impacting model training speed and practicality. It involves managing communication overhead, the data exchanged between clients and the server, communication costs, and the time and resources required for data transfer. Techniques such as model compression and efficient aggregation methods help minimize these costs, improving overall system efficiency [133].

6 The Process for Federated Learning in Mental Health

The steps required to set up a federated learning system between a central server and a mental health facility (MH facility) are outlined in the sequence diagram in Fig. 12. The MH Facility requests the Federated Learning Setup from the Central Server after identifying the problem and process objectives. The MH Facility's desired model architecture is then described.

The central server verifies the architecture needed for the Federated Learning Process. The MH Facility then prepares the data, separating it into training and validation datasets before forwarding the anonymized, pre-processed data to the central server. The central server develops a global model, and the MH Facility modifies a local model in the Federated Learning Architecture. Secure lines are available for communication between the MH Facility and the central server.

The Central Server requests a model review, and the MH Facility employs privacy preservation strategies. Iteratively, the central server asks for more training depending on the MH Facility's evaluation results. The revised model is subsequently transmitted back to the central server.

After a successful development phase, the global model is distributed from the central server to the MH Facility. Ethics and compliance are ensured throughout the process, and the MH Facility acts to address bias and injustice. The Federated Learning Architecture is updated as needed to address difficulties in healthcare while upholding ethical principles and privacy.

7 Benefits of Federated Learning in the Mental Health Field

FL emerges as a transformative approach in the mental health domain, offering a range of pivotal advantages, as shown in Fig. 13. Regarding privacy issues, FL's main advantage is that this allows the users' sensitive mental health data to stay in separate devices and not be aggregated into a single place. This case refers to sensitive data, and thus, it has crucial privacy issues. FL enhances data security by minimizing the chances of a data breach that could lead to undesirable results such as discrimination, stigmatization, and other mental health issues. Further, FL offers collaborative learning by training models and several peers' thoughts but shields individual information. Thus, a participatory approach is significant for mental health research [134–136].

In addition, FL supports heterogeneity for mental health data, allowing model training with diverse inputs that are adaptive to multiple mental health situations among populations and demographics. Routine screening of mental health indicators in FL for edge devices and wearables supports dynamic and responsive mental health analysis. Further, FL reduces communication inefficiencies by only sharing models' updates or aggregated data in costly or low bandwidth environments [137–139].

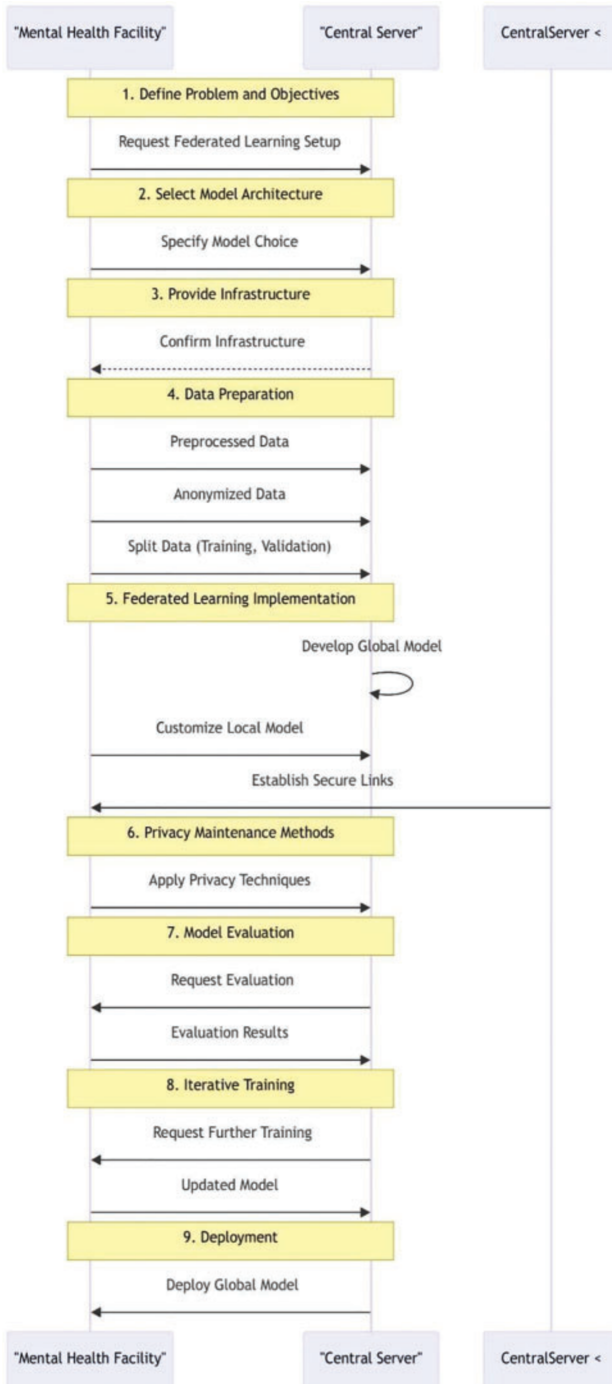

Figure 12: The sequence diagram for establishing federated learning in mental health application

FL is ethically sound as it aligns with notions of user autonomy that allow individuals to participate in mental health research and own their data. It can support a few research teams undertaking large-scale mental health research worldwide and allow cross-research teams to analyze trends and patterns collectively [140]. The continuous refinement of models based on insights from different participants underscores FL's adaptability in the ever-evolving mental health field. Overall, FL significantly benefits mental health applications, paving the way for more effective, collaborative, and privacy-preserving approaches to mental health research and analysis [141].

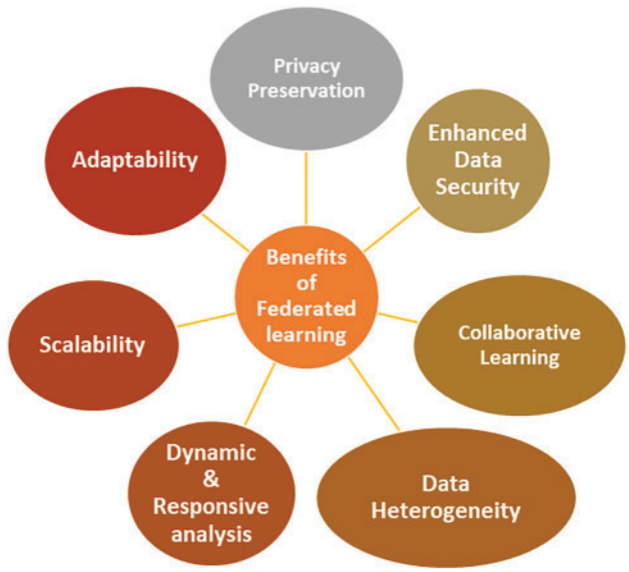

Figure 13: Benefits of federated learning

8 Future Challenge Using Federated Mental Health Learning

Although FL holds great results in advancing mental health research and applications, several challenges and considerations must be focused on to unlock its full potential. The future challenges related to federated learning in mental health are illustrated in Fig. 14.

8.1 Heterogeneity of Data

Mental health data can vary widely regarding types of disorders, severity, and individual experiences. Handling this heterogeneity in Federated settings is challenging, and developing models that generalize well across diverse mental health conditions remains a key concern [142].

8.2 Data Imbalance

Some mental health conditions can be more prevalent than others, leading to imbalanced datasets. Ensuring fair representation of all conditions in federated learning models is crucial for accurate and unbiased predictions [143].

8.3 Model Interpretability

For instance, the federated learning schemes involving deep neural networks could be confusing. Successful federated learning adoption mandates creating models all involved mental health specialists know and accept as reliable [144–146].

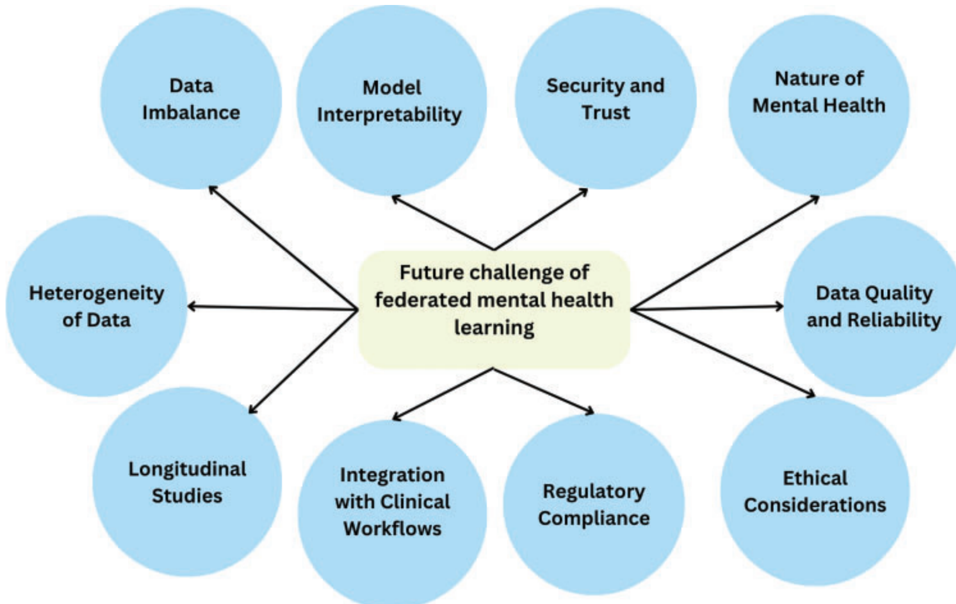

Figure 14: The future challenge of federated mental health learning

8.4 Security and Trust

The use of federated learning involves several entities working together. Security of models' updates, poisoning attacks mitigation, and trust between stakeholders are still existing hurdles for Federated mental health learning [147–149].

8.5 Dynamic Nature of Mental Health

Mental health conditions are dynamic. Creating federated models responsive to transient changes in mental health states and treatment responses necessitates perpetual assessment and model alteration [150–152].

8.6 Data Quality and Reliability

As far as data from different devices is concerned, it is necessary for federated learning to ensure that its quality and reliability are appropriately maintained. It is critical for the FL's effectiveness in terms of mental health to address issues such as noise, outliers, and anomalies [153].

8.7 Ethical Considerations

Federated learning in mental health raises ethical considerations related to consent, transparency, and the responsible use of data. Balancing the benefits of collaborative research with protecting individual privacy and rights is an ongoing challenge [154].

8.8 Regulatory Compliance

Stringent privacy regulations frequently govern mental health data. Federated Learning must conduct while ensuring compliance with Health Insurance Portability and Accountability Act standards. HIPAA in the United States presents significant challenges that require careful attention [155].

8.9 Integration with Clinical Workflows

Integrating federated learning models into existing clinical workflows and electronic health record systems is crucial for their real-world applicability. Overcoming technical and organizational barriers for smooth integration remains challenging [156].

8.10 Longitudinal Studies

Federated learning models may benefit from longitudinal data to capture the progression of mental health conditions over time. Designing and conducting federated longitudinal studies pose logistical and methodological challenges [157].

Addressing these challenges will require interdisciplinary collaboration involving researchers, mental health professionals, data scientists, and policymakers. Overcoming these obstacles will contribute to the responsible and effective use of federated learning in advancing mental health research and applications.

9 Conclusions

This extensive study underscores the growing connection between technology and, more specifically, federated learning in mental health applications to combat the global burden of mental performance. Many applications arise from the growing need for mental health support, but privacy concerns regarding sensitive mental health data have been a significant hindrance.

In this context, this article investigates different federated learning models related to mental health topics. The advantages of federated learning in mental health applications are highlighted in this research. As the study looks forward, it proposes additional work to improve and modulate federated learning techniques especially for mental health purposes. This could, for example, entail the investigation of trainable predictive models via more advanced federated learning frameworks or adaptation of algorithms to mental health data or even, evaluating implications pertaining to continuity in utilizing federated learning for support on mental health. This research adds to the continually shifting mental health apps terrain by providing insight into status and direction for future work, highlighting federated learning as a crucial entity in maintaining privacy, safety, and cooperation in the world of digital mental health care.

However, one limitation of this study is that the applications of federated learning in mental healthcare are still in their early stages, with limited real-world implementations and long-term evaluations. Security and privacy concerns remain critical, as federated learning models are not entirely immune to data leakage or adversarial attacks.

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