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Role of deep learning in cognitive healthcare: Wearable signal analysis, algorithms, benefits, and challenges ☆

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A B S T R A C T

Deep Learning (DL) offers promising solutions for analyzing wearable signals and gaining valuable insights into cognitive disorders. While previous review studies have explored various aspects of DL in cognitive healthcare, there remains a lack of comprehensive analysis that integrates wearable signals, data processing techniques, and the broader applications, benefits, and challenges of DL methods. Addressing this limitation, our study provides an extensive review of DL's role in cognitive healthcare, with a particular emphasis on wearables, data processing, and the inherent challenges in this field. This review also highlights the considerable promise of DL approaches in addressing a broad spectrum of cognitive issues. By enhancing the understanding and analysis of wearable signal modalities, DL models can achieve remarkable accuracy in cognitive healthcare. Convolutional Neural Network (CNN), Recurrent Neural Network (RNN), and Long Short-term Memory (LSTM) networks have demonstrated improved performance and effectiveness in the early diagnosis and progression monitoring of neurological disorders. Beyond cognitive impairment detection, DL has been applied to emotion recognition, sleep analysis, stress monitoring, and neurofeedback. These applications lead to advanced diagnosis, personalized treatment, early intervention, assistive technologies, remote monitoring, and reduced healthcare costs. Nevertheless, the integration of DL and wearable technologies presents several challenges, such as data quality, privacy, interpretability, model generalizability, ethical concerns, and clinical adoption. These challenges emphasize the importance of conducting future research in areas such as multimodal signal analysis and explainable AI. The findings of this review aim to benefit clinicians, healthcare professionals, and society by facilitating better patient outcomes in cognitive healthcare.

1. Introduction

Cognitive diseases refer to a wide range of disorders impacting the brain and central nervous system. With varieties of cognitive issues leading to neurological conditions, they disrupt various aspects of human life, including perception, judgment, reasoning, memory, and physical abilities [1]. Deep learning is a subfield of Machine Learning (ML) that excels at handling unstructured data like text and images directly, identifying distinctive features that separate different data categories [2–4]. This eliminates the need for manually identifying features, as the architecture autonomously learns and improves its understanding, necessitating a larger dataset [5]. DL has grown as a highly effective and

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significant approach in cognitive healthcare, making use of wearable signals like Electroencephalography (EEG), Electrocardiography (ECG), Electromyography (EMG), and accelerometry to collect crucial data for analysis [6–9]. To develop a complete picture of cognitive health, these signals offer important information on a variety of factors, such as heart rate, muscular activity, movement, and physical activity, all of which are crucial [10,11]. Wearable signal preprocessing is necessary to prepare them for analysis. To improve the signal quality, EEG signals, for instance, frequently go through processes like noise reduction, artifact removal, and filtering [12,13]. Filtering, normalization, and feature extraction are used in ECG data to highlight certain cardiac rhythms [11,14]. Filtering and normalizing are used in the case of EMG signals to remove noise and collect data on muscle activity [15]. In order to learn more about movement patterns and activity levels, accelerometry data is often filtered and treated to a variety of feature extraction techniques [16,17].

DL methods, including convolutional neural networks, recurrent neural networks, and LSTM networks have various applications in cognitive healthcare. The use of DL models for the analysis of EEG and ECG data allows for the early detection of illnesses such as Parkinson's and Alzheimer's [18–20]. Emotion detection uses wearable signals to decipher emotional states and is crucial for tracking mental and emotional wellness [10,21]. In order to assess sleep quality and spot sleep problems, sleep analysis also requires analyzing data from wearables [22]. Stress monitoring tracks physiological signals to gauge stress levels and offer real-time feedback [23,24]. Neurofeedback employs DL to provide real-time brain activity feedback for cognitive training and rehabilitation [14,25]. Additionally, DL models are utilized in dementia prediction and diagnosis, analyzing multiple wearable signals to enable early detection and personalized treatment plans [26,27]. Although DL shows great promise in cognitive healthcare, it encounters certain challenges. Overcoming obstacles such as the requirement for extensive and diverse datasets, ensuring model interpretability, and addressing ethical issues associated with data privacy and security are essential [28–30]. In the future, the advancement of DL in cognitive healthcare involves several key directions. Developing explainable AI models becomes crucial to enhance the understanding of model decisions [31,32]. Integrating multi-modal data enables more comprehensive analysis and a more holistic approach to patient care [33]. Ensuring data privacy and security through robust cryptographic algorithms and secure authentication schemes is essential to safeguard sensitive health information within these AI-driven systems [34,35]. Optimizing DL architectures for resource-constrained devices will improve accessibility and usability in various healthcare settings {[36,28]. Conducting large-scale clinical trials to validate the effectiveness of DL-based diagnostic and therapeutic approaches is vital for establishing their reliability and real-world applicability [37,38]. By addressing these challenges and exploring new avenues, DL can significantly revolutionize cognitive healthcare, enabling early detection, personalized treatments, and ultimately enhancing patient outcomes.

A thorough review of existing literature reveals a significant gap in comprehensive studies exploring DL applications in cognitive healthcare. While numerous studies address individual aspects, such as specific cognitive healthcare applications or wearable technologies, there is a notable gap in research that integrates these areas into a cohesive investigation. In particular, there is no in-depth analysis of how DL can be utilized to address a broad spectrum of cognitive healthcare challenges, alongside a discussion of the associated benefits and limitations. Table 1 presents a summary and comparison of recent literature reviews on DL in cognitive healthcare, pertaining to the topic explored in this paper. However, prior research has not fully addressed critical aspects such as the integration of wearable signal modalities, the pre-processing techniques necessary for optimizing these signals for DL, the variety of DL techniques/settings employed, and their specific benefits in cognitive healthcare. Additionally, challenges faced by DL algorithms in this domain have not been thoroughly examined. This paper addresses these research gaps by providing a comprehensive analysis of the widely used wearable signal modalities in DL applications for cognitive healthcare. It offers valuable insights into the pre-processing techniques that enhance DL performance, discusses the practical benefits of applying DL to cognitive health issues, and critically examines the challenges that must be addressed to advance this field. This novel approach provides a more holistic understanding of the potential and limitations of DL in cognitive healthcare, motivating further research and development in this emerging area.

The objectives of this study were defined based on the following research questions:

a) Why has DL in cognitive healthcare become prominent rapidly and what effects does this have on healthcare delivery models and patient care?
b) How do preprocessing techniques improve wearable signal quality and trustworthiness?
c) What are the most significant applications of DL in cognitive healthcare and their limitations?
d) When it comes to data quality and management, what are some of the primary challenges that must be overcome when implementing DL methods?
e) What methods are being used to deal with the difficulties of interpretability and model generalization in the field of cognitive healthcare?
f) How has research and development in DL contributed to improved cognitive healthcare services and patient outcomes through data analysis and decision-making processes?

To facilitate a comprehensive discussion, the paper is structured as follows: Section 2 provides an in-depth overview of the methodological approaches used to assemble, organize, and investigate the relevant data for this review. Section 3 explores wearable signal modalities and their pre-processing techniques. Section 4 delves into various DL methods used for cognitive issues. Section 5 discusses the diverse applications of DL in different cognitive diseases. Section 6 outlines the benefits of DL techniques in cognitive healthcare, highlights key challenges currently encountered by these methods, and offers recommendations for future research. Future directions to address the challenges are provided in Section 7 in order to advance cognitive healthcare research. Section 8, finally, concludes the paper by summarizing the overall discussion on the landscape of DL in cognitive healthcare.

2. Methodology

This extensive literature review is designed to explore the utilization of DL methods in cognitive healthcare, with a focus on wearable signals, data processing, applications, and the related challenges and opportunities. The study adopts an integrative approach by thoroughly examining and assessing high-quality research papers from reputable sources, including Google Scholar and Scopus, as well as journals from esteemed publishers like Elsevier, Springer, Nature, IEEE, and ACM. To ensure a thorough assessment, substantial contributions from lesser-known yet equally credible publishers such as Frontiers, Tech Science Press, and IOP Publishing have also been included. The literature search was systematically conducted using carefully selected keywords pertinent to the research topic. The key terms encompassed "Deep learning," "Cognitive healthcare," "Cognitive disorders," "Wearable signals," "Data processing," "Applications of deep learning," and "Deep learning in cognitive healthcare." Boolean logic operators (OR, AND, NOT) were employed to refine and broaden the search results, using combinations such as "Cognitive impairment OR cognitive disorders" and "Deep learning AND cognitive healthcare." The search was mainly targeted on studies published in English within the last five years (2020 and onwards). Additionally, relevant papers were identified through a detailed examination of the references and bibliographies of the selected publications. The selected

Table 1
Comparative analyses of the topics explored in this review study versus those in recent review studies.

Review study	Wearable signal modalities	Pre-processing techniques of signals	DL techniques	Applications of DL in cognitive healthcare	Challenges
Our study	✓	✓	✓	✓	✓
[39]	✓ (brief)	×	✓ (brief)	✓	✓
[40]	✓	✓	×	Only mild traumatic brain injuries	✓ (brief)
[1]	×	×	✓ (brief)	✓	✓ (brief)
[4]	×	×	✓	✓	✓ (brief)
[41]	×	×	✓ (brief)	✓	×
[8]	×	×	✓	✓	✓
[42]	×	×	✓	✓	✓
[28]	✓ (brief)	×	×	✓	✓
[43]	✓	✓	✓ (brief)	✓	✓ (brief)
[44]	×	×	✓	✓ (brief)	×

Table 2
Criteria for selecting relevant literature.

Criteria	Inclusion requirements	Exclusion requirements
Focus	Research should concentrate on the role of DL in cognitive healthcare, including its applications, associated wearable devices, benefits, and challenges.	Studies not focusing on DL, wearable signals, cognitive disorders, or cognitive healthcare, or those that do not specifically address the involvement of DL methods in cognitive healthcare, are excluded to avoid bias.
Recency	Literature must be published within the last five years to ensure it reflects recent advancements and developments in the field.	Literature published before the last five years is excluded to ensure the inclusion of recent and relevant developments.
Content	Selected publications should be scientific, peer-reviewed, and effectively address the research inquiries. Priority is given to studies that offer a comprehensive understanding of the topic, including numerical and experimental studies, meta-analyses, and systematic reviews.	Even if scientific and peer-reviewed, publications that do not adequately cover the specified keywords or research inquiries are not considered.
Grey Literature	Grey literature is considered if it shows significant potential value and relevance to the topic.	Grey literature that is repetitive or lacks adequate references and contextual detail is excluded. Conference proceedings are considered only to a limited extent in this analysis.

papers were rigorously evaluated based on their abstracts, introductions, and conclusions, and categorized according to the following criteria:

- Emphasis was placed on peer-reviewed articles from the previously mentioned reputable sources and other equally credible publishers.
- Preference was given to published works by leading researchers in the field to guarantee the quality and relevance of the review.
- A proper balance between latest developments and foundational studies was maintained to provide a well-rounded perspective.
- Pivotal papers cited in subsequent research were traced back to their original sources to ensure the inclusion of pioneering contributions.

The literature search for this in-depth review utilized an iterative process to maximize its effectiveness. Initially, a preliminary search was conducted using selected keywords, and the results were analyzed to refine the search strategy. This refinement process included revising search terms, integrating additional relevant keywords, and altering Boolean operator combinations to strike a balance between sensitivity and specificity. Relevant phrases identified during the preliminary review were also incorporated into the search strategy to obtain more focused literature. The search was frequently updated to include the most recent publications, ensuring the review remained comprehensive. Despite efforts to limit and select the literature, the exclusion criteria were acknowledged as highly subjective. Scientific, peer-reviewed publications were assessed based on these criteria to ensure that only the most relevant and informative studies corresponding to the specified keywords were included. Publications were excluded if they lacked adequate discussion of the selected keywords or failed to address them thoroughly. Additionally, gray literature was not considered in this study if it provided redundant results or lacked the required references and contextual details. To prioritize high-quality sources, conference proceedings were reviewed only to a limited extent. To ensure consistency and reliability in the exclusion process, the authors utilized a test-retest strategy to mitigate possible bias. Studies were randomly selected from the main research pool to avoid potential bias and ensure that the subset selected for reassessment accurately represented the entire scope of the literature under consideration. Then the authors performed multiple iterations of comprehensive checks on the chosen studies, rigorously assessing the relevance of the exclusion criteria. These repeated evaluations aimed to verify the validity of the exclusion decisions and reduce the impact of subjective assessments. Table 2 summarizes the primary inclusion and exclusion criteria that formed the foundation of this research.

3. Wearable signal modalities & preprocessing

Wearable signal modalities refer to the diverse array of signals gathered by wearable devices. Wearable devices can be defined as technological devices that are designed to be worn directly on the human body or integrated into clothing [45,46]. EEG, ECG, and EMG are widely used sensing modalities in wearable devices [47,48] as well as accelerometry for motion data. Wearable signal analysis is increasingly being integrated with DL techniques to advance the monitoring of cognitive health. DL models are adept at processing and extracting meaningful insights from complex physiological signals collected by wearable devices. For example, Electrodermal Activity (EDA) data can be analyzed to predict the severity of depression, while Photoplethysmography (PPG) technology is used to monitor cardiovascular health [49,50]. Leveraging DL to analyze these physiological signals greatly improves the accuracy of health assessments and predictions, allowing for more precise evaluation of brain activity, heart function, and muscle responses in cognitive healthcare. In order to ensure that the obtained data is accurate and reliable for analysis and interpretation, the wearable signal modalities need to be preprocessed to eliminate noise, artefacts, and inconsistencies that could distort the data. DL can analyze these signal modalities by automatically identifying complex patterns and characteristics in the preprocessed data, thereby improving model performance and usability. Fig. 1 provides an overview of the complete workflow for using

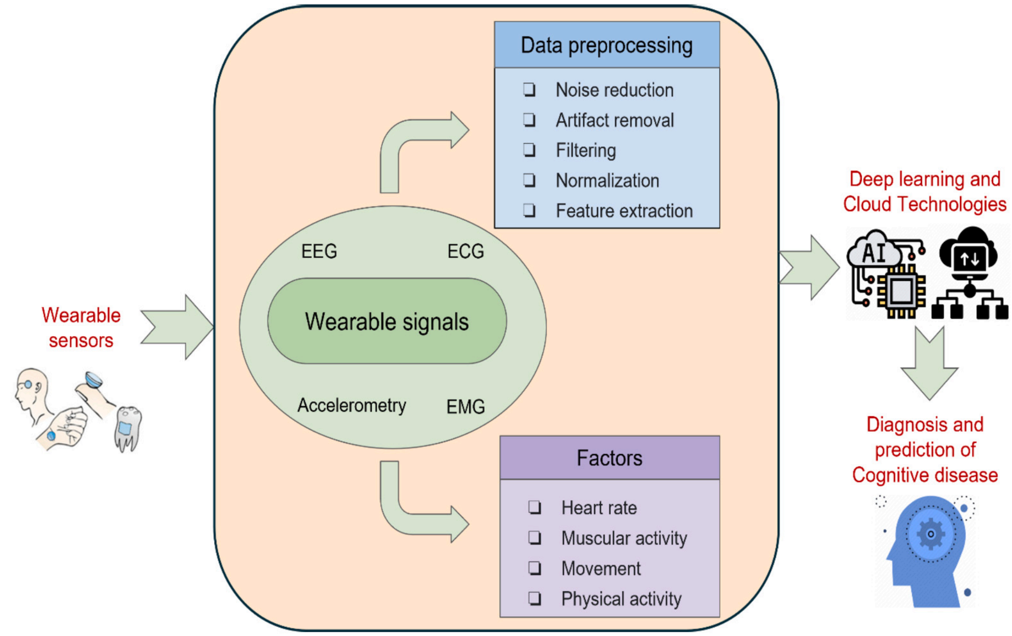

Fig. 1. Overview of the complete workflow for using DL in the diagnosis and prediction of cognitive diseases.

DL in the diagnosis and prediction of cognitive diseases, encompassing the collection of wearable signals and preprocessing methods. A concise overview of recent research discussions regarding wearable signal types and preprocessing methods is shown in Table 3.

DL algorithms have significantly transformed the processing of wearable signals by offering robust automatic feature extraction from complex, high-dimensional sensor data. Techniques like auto-encoders and Deep Belief Networks (DBNs) excel in unsupervised learning, effectively reducing dimensionality and suppressing noise, though they may struggle to capture the most relevant features. Similarly, Restricted Boltzmann Machines (RBMs) are capable of unsupervised feature extraction but face challenges with high parameter initialization, leading to long computation times that limit their real-time applicability in wearable signal processing [51]. On the other hand, CNNs are widely used for their hierarchical feature extraction and ability to leverage pre-trained models for fast convergence, though they require fixed-size inputs and extensive labeled data [52]. Meanwhile, RNNs and LSTMs excel at modeling time dynamics in sensor streams, though their high computational demands and sensitivity to vanishing gradients make them challenging to train [53]. Generative Adversarial Networks (GANs) are valuable for augmenting limited datasets, while reinforcement learning is emerging in specific wearable signal applications like modeling muscle and arm movements, though it remains difficult and time-intensive to train [54]. Ultimately, selecting the appropriate DL approach depends on several factors, such as the complexity of the problem, dataset size, data quality, and available computing resources.

3.1. Electroencephalography

EEG is a technique used in electrophysiology that collects and records the electrical patterns and signals generated by the brain [55]. When a collection of small, stimulated post-synaptic potentials produced by pyramidal neurons in the brain's cortical layers occurs, it results in electric changes in the range of tens of microvolts (μV) that propagate to the scalp. These differences are captured by EEG, which serves as a means to detect neural activity. EEG recordings can be employed to investigate a broad spectrum of brain activities [56]. Mainly, a number of electrodes are positioned on the scalp in order to capture and measure voltage differences [57]. However, technological advancement allowed the incorporation of EEG sensors in wearable devices like headsets and hand bands. EEG is extensively employed in clinical contexts and cognitive and neuroscience investigations to examine many aspects such as sleep patterns, epilepsy, Attention-Deficit/Hyperactivity Disorder (ADHD), an individual's exhaustion levels, mental workload, mood, and emotions [56]. The utilization of DL algorithms has demonstrated potential in extracting significant information from EEG signals, enhancing its potential benefits for cognitive health.

Epilepsy is a health condition that affects our brain and can cause cognitive impairment, like memory deficits [58]. Using EEG signals, epilepsy can be detected. One study by Gao et al. [59] used Deep Convolutional Neural Networks (DCNNs) to develop a novel epileptic EEG Signal Classification (EESC), a reliable method for identifying EEG signals to diagnose epilepsy. The study aimed to enhance the accuracy of classifying various epileptic states using multichannel EEG signals, mainly focusing on identifying four different states of epilepsy: seizure, preictal I, preictal II, and interictal. Three DCNNs, ResNet152, Inception-v3, and Inception-ResNet-v2 were employed in this study. The EESC approach performed better compared to other approaches in terms of specificity and sensitivity. It exhibited a high sensitivity of 95.8%, 93.6%, 92.3%, and 97.8%, and specificity of 99.3%, 97.1%, 97%, and 99.2% in accurately categorizing the four epileptic states, namely seizure, preictal I, preictal II, and interictal, indicating that the proposed DL method outperformed the three individual DCNN models. Nevertheless, the classification of preictal I and preictal II states remains less reliable compared to the other two types of epilepsy. More advanced feature extraction techniques can be used to capture the subtle differences between the two preictal states.

Another study employed a DL method to analyze EEG data of children who have schizophrenia [60]. It developed an automated method to differentiate between children vulnerable to schizophrenia and children usually developing schizophrenia by analyzing EEG data with ML and DL techniques. Hand-engineered features taken from EEG recordings were used for the conventional ML algorithms K-Nearest Neighbor (KNN), Decision Tree (DT), and Support Vector Machine (SVM). Moreover, the Recurrent Convolutional Neural Network (R-CNN) was used to model the unprocessed EEG data without manually creating features. KNN, SVM and DT were all found to have accuracy levels below 45% on average during testing. On the contrary, the R-CNN achieved an average accuracy of 89.98% for the validation and 69.53% for the test sets, indicating that the DL technique outperforms the traditional ML techniques. Nevertheless, the model had difficulty performing adequately for all people due to variations in how their brain activity patterns were categorized. Researchers may consider employing particular methods to assist the model in comprehending these variations and making more precise predictions.

A DL model was developed by Casciola et al. [61] to analyze EEG data collected from headbands and polysomnography to classify different stages of sleep. The authors used DL architecture combining CNN and LSTM layers for sleep stage classification where CNNs extracted spatial information, and LSTM layers captured temporal relationships in the EEG data. The DL sleep staging model demonstrated an accuracy of 74% on poor-quality headband EEG data, whereas the benchmark PSG obtained an accuracy of 77%. The performance of the model was also consistently high across all sleep phases, leading to a balanced accuracy that surpasses any previously evaluated ML method for classifying different sleep phases by around 20%. Though the DL model showed a high accuracy rate, the dataset size of the study was too small (12 participants). To increase the model's applicability and produce more precise sleep staging and potential diagnostic markers for neurodegenerative illnesses, future research should use larger and more varied datasets.

3.2. Electrocardiogram

An ECG is a type of non-linear, quasiperiodic time series that is utilized to examine the muscular and electrical activity of the heart and provides details about rhythm and heart rate [62]. The ECG signal is generated by the depolarization and repolarization processes of the ventricular and atrial muscles of the heart [63]. The ECG signal is composed of three unique elements: the QRS complex, which reflects a mix of atrial repolarization and ventricular depolarization; the P wave, which corresponds to the depolarization of the atria; and the T wave, which indicates the repolarization of the ventricles [63]. Gel electrodes are primarily utilized for capturing ECG signals [64]. Nowadays, the incorporation of wearable ECG sensors into garments, mobile devices, and accessories can benefit individuals susceptible to health risks and may result in favorable health consequences [65]. The integration of ECG-AI with wearable sensors and devices has been employed to examine a range of cardiac diseases, such as cardiac arrest, stroke, atrial fibrillation, and heart failure.

A combined approach of LSTM and CNN was used by Zarei et al. [66] to analyze ECG signals to diagnose obstructive sleep apnea disease and to automatically extract pertinent characteristics from ECG data. The LSTM and CNN were used to extract temporal dependencies and spatial from the ECG signal, respectively. The performance of the proposed approach was evaluated on two datasets, the UCDDB and Apnea-ECG datasets. The method achieved average accuracies of 97.21% for per-segment classification and 100% for per-recording classification, respectively, when applied to the Apnea-ECG dataset. When the UCDDB dataset was utilized for analysis, the DL model exhibited notable performance metrics. Specifically, the model achieved a sensitivity of 90.69%, average accuracy of 93.70%, and a specificity of 95.82%. These results indicate that the DL model possesses the capability to effectively evaluate ECG signals with a high degree of precision. Although the proposed model exhibited promising results on the given datasets, the study did not explicitly investigate the model's performance when tested with a wider range of diverse and noisy ECG data, which is frequently seen in actual clinical environments.

Another study by Peimankar et al. [67] also used CNN and LSTM to develop a DL algorithm to analyze ECG signals. A CNN-LSTM model was proposed to accurately classify three different ECG wave patterns, namely the QRS complex, the P-wave, and the T-wave, inside each cardiac cycle. The model underwent training and validation using a dataset consisting of 105 ECG records. The model exhibited an average precision of 95.68% and an average sensitivity of 97.95% through the utilization of a layered 5-fold cross-validation technique. Although the proposed model demonstrates a high level of precision in detecting the QRS complex along with the P-wave and T-wave, which is advantageous for identifying cardiac arrhythmias, it does not possess the capability to classify any abnormal waveform present in the ECG data.

Ullah et al. [68] used both 1D and 2D CNN to analyze ECG signals and classify different arrhythmia types. The authors proposed a robust methodology employing DL algorithms that can accurately categorize the ECG data, even when it is contaminated by the noise from the surroundings. Classification-relevant characteristics can be extracted from the signal by directly processing the ECG data with 1D CNN. In contrast, the 2D CNN converts the 1D ECG signal into 2D pictures through the Continuous Wave Transform (CWT). This process holds the potential to enhance accuracy by improving the representation of the signal. The proposed 1D model attained a classification accuracy of 97.38%, whereas the 2D models reached an accuracy of 99.02% when evaluated on the publicly accessible Massachusetts Institute of Technology-Beth Israel Hospital (MIT-BIH) arrhythmia database. However, the presence of multichannel ECG signals was not taken into consideration by the model. The robustness of arrhythmia classification models could be improved by using multichannel ECG signals.

3.3. Electromyographic

The EMG signal represents the voltage of the electrical field produced by the activation of the external fiber membranes of the muscle [69]. The acquisition of EMG signals is facilitated by the placement of sensors on the surface of the skin [70]. EMG signals can detect muscle dysfunction, muscle damage, and nerve damage resulting from neurological and muscular disorders [71]. One advantage of EMG signals compared to EEG and ECG is the broader frequency spectrum of EMG signals, which spans from 5 Hz to 2 kHz, whereas EEG and ECG signals typically fall below 100 Hz [71]. Nevertheless, EMG signals exhibit significant variability due to age, fat layers of skin, muscle strength, gesture, and motor unit pathways [72]. Consequently, the analysis of these signals poses considerable challenges.

A DL approach was implemented in a study conducted by Ozdemir et al. [73] to analyze EMG signals to classify hand gestures. This study was carried out to create and assess a methodology based on DL and Short Time Fourier Transform (STFT) for real-time classification of upper limb surface electromyography (sEMG) signals, specifically targeting the classification of seven distinct hand motions. Using surface bipolar electrodes, the study obtained 4-channel EMG data from 30 healthy individuals between the ages of 18 and 25. Following acquiring the one-dimensional sEMG data, the STFT technique was employed to generate two-dimensional spectrogram images. The ResNet-50 architecture, a modified version of CNNs was utilized to analyze the EMG data. The architecture of each ResNet block has three layers, which employ convolutional layers with dimensions of (1x1), and (3x3) to process the input data. The proposed model achieved an F1 score of 99.57% and a test accuracy of 99.59% across seven distinct hand gestures. The study lacks a thorough consideration of the potential effects of various spectrogram parameters, for example, window length and the discrete Fourier Transform (DFT) utilized in the STFT process.

In a different work by Chung et al. [74], DL techniques were applied for the real-time classification of hand motions from a wearable hand band device. The DL methods were used to build a generalizable system that automatically extracts features from EMG data and correctly classifies hand gestures without requiring user-specific training. The proposed model sought to recognize five hand gestures in real-time: the fist, the left and right waves, the wide fingers, and the double tap, with possible applications in human-machine interaction. The study used Myo Armband which is a device equipped with 8 EMG sensors. Among the dataset consisting of 120 users, half of the data was utilized for the purpose of model development, while the remaining data was employed to assess and evaluate the performance of the model. A feed-forward multiple-layered neural network (NN) was utilized to analyze and categorize the EMG signals collected from the Myo Armband. The suggested model could recognize the same five gestures as the Myo Armband's unique recognition system with 85.08±15.21% average identification accuracy and 3±1 ms response time. However, the model's design and feature extraction methods were specifically tailored to the attributes of the Myo Armband, making it less scalable to different hardware setups.

DL technique were also applied in a study by Yu et al. [75] to analyze EMG signals and predict strokes. Real-time EMG data were collected from daily activities involving the left biceps, femoris and right biceps, gastrocnemius muscles using a medical device at 1500 Hz. This data was further used to detect and predict strokes employing both ML algorithms such as Random Forest (RF) and DL algorithms, including LSTM. In this study, the diseased group comprised 287 stroke patients aged 65 or above who received rehabilitation therapy around a month after diagnosing of their condition. In contrast, the normal group comprised 271 people receiving therapy for different reasons than stroke. The RF model achieved a prediction accuracy of 90.38%, while the LSTM model had a higher accuracy of 98.958%. The DL approach outperformed the ML model. However, focusing solely on individuals aged 65 and older restricts the applicability of findings to younger populations. It may limit the predictive model's applicability to a wider age range.

3.4. Accelerometry

The term "accelerometry" refers to studying and analyzing acceleration-related data using accelerometers. Accelerometers are highly responsive motion sensors utilized for quantifying the intensity of acceleration along one or several axes. They are frequently employed in the analysis of human movement patterns and the identification of distinct activities, including walking, jumping, kicking, and throwing [76]. There are several applications for accelerometer data. For instance, accelerometry sensors can objectively measure how long, when, and how the reported pain from patients interferes with regular activities [77]. Additionally, an accelerometer-based wearable device that analyzes gait impairment can distinguish between different subtypes of dementia diseases [78]. Apart from that, accelerometry offers a scalable method for measuring sleep characteristics in clinical studies related to mental health and upper limb compensatory movements in individuals who have had a chronic stroke [79,80].

Deep Neural Networks (DNNs) and CNNs were employed by Nunavath et al. [81] to analyze accelerometry data from wearable sensors. The DL framework was developed in order to effectively classify various Activities of Daily Living (ADLs) performed by individuals. These movement patterns are obtained from information gathered by tri-axial accelerometer sensors worn on the wrist and hip. The study utilized two datasets: accelerometer data from 16 participants and eight volunteers. The initial dataset, sourced from the UCI Machine Learning Repository, included 14 ADLs, while the later dataset included 10 ADLs. Both the RNN and DNN models performed adequately on "unlabeled" data recognition, with a recall percentage of 94% and 64%, respectively. One of the potential areas for improvement is the small size of the dataset, which may affect the models' ability to correctly categorize movement patterns in more complicated and varied scenarios that need to be sufficiently represented in the current datasets.

Another study by Farrahi et al. [82] analyzed accelerometry data from wrist-worn devices. They developed a DL-based method to accurately categorize multiple 24-hour activity behaviors using raw accelerometry data collected from these devices. The data was gathered from 151 individuals. For classification, the primary DL framework employs signal-to-image conversion, transfer learning with ResNet101, and a Bidirectional Long Short-Term Memory (BiLSTM) network. The model's overall accuracy on the validation dataset was found to be 96.9%, while it was 98.2% on the test dataset. The scope of the study could be expanded by collecting accelerometry data from different body parts.

Using a DL technique, particularly CNN, Bringas et al. [83] analyzed accelerometry data from patients with Alzheimer's disease (AD). A predictive model was developed to reliably identify the stage of AD based on the mobility patterns of patients using accelerometer data from their smartphones. The dataset was comprised of accelerometer data collected over a week from 35 patients with AD. The patients carried Android smartphones with built-in accelerometer sensors freely during everyday activities. The DL framework employed convolutional layers for feature extraction, pooling layers for reducing data size, dropout layers to prevent overfitting, and fully connected layers for generating predictions. The CNN model classified the various phases of AD with high accuracy of 91%. Due to its one-week data collection timeframe, the study may not have captured the full range of AD development and patients' daily activities.

3.5. Data preprocessing techniques

Data preprocessing refers to transforming unprocessed or raw data into a clean data set [84]. The goal of data preprocessing is to enhance the training and validating process by effectively modifying and standardizing the complete dataset [85]. The data obtained from wearable signals are prone to noise interference. For instance, baseline wander, power-line interference, muscle artefacts, and channel noise may be present in ECG data [62]. Similarly, motion artefacts, power line interphase, and white gaussian noise might be reflected in EMG data [86]. By preprocessing the data, each of these issues could be resolved. Furthermore, the accuracy and reliability of a DL prediction model are heavily dependent upon data preprocessing. For instance, a CNN model can be affected by inaccurate or noisy training data [87].

Different functions of time series operation, namely, squeeze, stretch, shrink, and amplify were used by Kanani et al. [88] to preprocess ECG signals. A preprocessing technique was developed for a DL model to accurately classify arrhythmia from ECG signals. The MIT-BIH arrhythmia dataset was used for supervised learning, which contains ECG signals divided into five classes that reflect different cardiac states. Signal transformations such as squeezing, stretching, amplifying, and shrinking are applied during preprocessing to enhance the characteristic properties, resulting in variations added to the initial dataset and yielding a collection of 547,230 samples. The advantage of the data preprocessing is that these transformations preserve the quality and characteristics of the actual signals. The model attained a remarkably high accuracy rate of 99.12%. Although the "amplify" transformation is intended to increase signal amplitudes, it has the potential to amplify any noise present in the original ECG signals.

Data preprocessing techniques were utilized by Alo et al. [89] to analyze accelerometry data collected from a smartphone. DL based on stacking autoencoder was designed for precisely recognizing complicated human activities utilizing sensor data from smartphones. The dataset included 10 people who carried smartphones in their pockets and wrists while participating in a variety of 13 activities. Two methodologies, namely data cleaning and data segmentation, were employed for data preprocessing. Noise removal and filtering reduced noise and missing values from raw signal sensor data. Missing values were input using linear interpolation, which replaced them with earlier values. Data segmentation used a 2-second sliding window without overlap method, which helped to identify human activity. The study demonstrated a classification accuracy of 97.13% by employing the preprocessing approaches, in contrast to deep belief and standard ML algorithms. However, for some activities, such as those with varying durations, the fixed window size for data segmentation may not be the optimal choice. This could result in unsatisfactory feature extraction and activity identification.

In the preprocessing stage, Bouallegue et al. [90] employed a ML filter based on a Gated Recurrent Unit (GRU) inside the framework of RNNs, referred to as RNN-GRU. The authors developed a practical preprocessing stage to improve the quality of EEG signals. CNN was used to classify two neurobiological diseases, epilepsy and autism, from EEG signal data. The CNN model used in the study classified epilepsy with an accuracy rate of 100% and autistic disorder with a rate of 99.5% utilizing the proposed preprocessing technique. While the study used

Table 3
Recent studies surveyed on wearable signal modalities and preprocessing.

Wearable signal modalities and preprocessing	Study	objective	Algorithm/Model	Outcome (s)	Remarks
EEG	[59]	Enhancing the accuracy of classifying various epileptic states using multichannel EEG signals, mainly focusing on identifying four different states of epilepsy such as seizure, preictal I, preictal II, and interictal.	DCNNs	95.8%, 93.6%, 92.3%, and 97.8% sensitivity and 99.3%, 97.1%, 97%, and 99.2% specificity in accurately categorizing the four epileptic states	The two Preictal (I and II) states are not classified as accurately as the other two states.
	[60]	Creating an automated method to differentiate between children vulnerable to schizophrenia and children usually developing schizophrenia by analyzing EEG data	R-CNN	Average accuracy of 89.98% for the validation set and 69.53% for the test set	The model had difficulty performing adequately for all people due to variations in how their brain activity patterns were categorized.
	[61]	Developing a DL method to analyze EEG data collected from headbands to classify different stages of sleep	CNN and LSTM	74% accuracy	Though the novel DL model showed a high accuracy rate, the dataset size of the study is too small (12 participants).
ECG	[66]	Developing a DL-based framework that could extract relevant features automatically from ECG signals to diagnose OSA disease	CNN and LSTM	Average accuracies of 97.21% for per-segment and 100% for per-recording classification for the Apnea-ECG dataset; 93.70% average accuracy, 90.69% sensitivity, and 95.82% specificity on the UCDDB dataset.	The model's performance should be explicitly investigated when tested with a wider range of diverse and noisy ECG data.
	[67]	Developing a model to accurately classify three different ECG wave patterns, namely, the QRS complex, the P-wave and the T-wave, inside each cardiac cycle	CNN and LSTM	Average sensitivity of 97.95% and average precision of 95.68%	The model does not possess the ability to classify any abnormal waveform present in the ECG data.
	[68]	Introducing a reliable method utilizing DL techniques that can correctly analyze the ECG signals to classify different arrhythmia types, even in the presence of noise from the surroundings	1D and 2D CNN	Accuracy of 1D model is 97.38% and 2D model is 99.02%	The presence of multichannel ECG signals must be accounted for when developing the model.
EMG	[73]	Implementing a methodology based on DL and STFT for real-time classification of upper limb sEMG signals, specifically targeting the classification of seven distinct hand motions.	ResNet-50 architecture, a modified version of CNNs	99.59% test accuracy and 99.57% F1 score	The potential implications of the several spectrogram parameters, like window length and the DFT used in the STFT method, were not carefully considered.
	[74]	Applying DL methods to build a generalizable system that automatically extracts features from EMG data and correctly classifies hand gestures without requiring user-specific training	Feed-forward multilayer NN	85.08±15.21% average accuracy and 3±1 ms response time	The design and feature extraction methods of the model, specifically developed for the Myo Armband, may limit its adaptability to other hardware setups.
	[75]	Applying ML and DL on real-time EMG data collected from daily activities involving the left biceps, femoris and right biceps, gastrocnemius to detect and predict strokes	RF and LSTM	90.38% accuracy for RF; 98.958% accuracy for LSTM	Focusing on 65-year-olds limits the predictive model's applicability to younger demographics.
Accelerometry	[81]	Building a DL model in order to effectively classify various ADLs	DNNs and CNNs	94% and 64% recall for RNN and DNN, respectively	A small dataset may hinder models' ability to classify movement patterns in more complex conditions.
	[82]	Developing DL architecture for correctly categorizing several 24-hour activity behaviors from raw accelerometry data gathered from wrist-worn devices	ResNet101 and BiLSTM	96.9% validation accuracy and 98.2% test accuracy	Accelerometry data from multiple body parts could extend the scope of the study.
	[83]	Creating a predictive model to classify the stage of AD based on the mobility patterns of patients using accelerometer data from their smartphones	CNN	91% accuracy	A short data collection period may not capture the full range of AD progression and patient activities.
Data preprocessing	[88]	Developing a preprocessing technique for a DL model to classify arrhythmia from ECG signals accurately.	Different functions of time series operation, namely, squeeze, stretch, shrink and amplify	99.12% accuracy	Signal amplitudes can be improved with the "amplify" transformation, but this may also increase background noise in the original ECG signals.
	[89]	Designing a DL model based on stacking autoencoder for precisely recognizing complicated human activities utilizing wearable sensor data	Data cleaning and segmentation	97.13% classification accuracy	Data segmentation using a constant window size may not be ideal for activities with variable durations.
	[90]	Introducing a practical preprocessing stage to improve the quality of EEG signals and classifying two neurobiological diseases, epilepsy and autism, from EEG signal data	RNN-GRU and CNN	Accuracy rates of 100% for epilepsy and 99.5% for autism	The RNN-GRU preprocessing method could be explored on different wearable signals such as ECG, EMG, and accelerometry.

the RNN-GRU preprocessing technique to evaluate EEG signals, future research might investigate the effectiveness and reliability of this technique to other wearable signals, including ECG, EMG, and accelerometry.

4. DL methods in cognitive healthcare

Advancements in medical technology have ushered in the era of big data in the biomedical field, which is now driven by ML techniques [43,91]. Among these cutting-edge approaches, DL stands out as it can autonomously extract intricate and robust features from data without requiring manual feature engineering. Within the medical domain, DL has assumed a significant role, particularly in cognitive healthcare, with vast prospects for application [4,8,41]. Its ability to handle and analyze massive and intricate datasets, including medical images, genomic information, and patient records, has expedited the pace of discovery and diagnosis. By detecting elusive patterns and correlations in data, DL aids in the early identification of neurological disorders. Additionally, these models hold the capability to forecast treatment responses and disease progression, opening the door for customized and targeted therapies. Through improved accuracy and efficiency in diagnostics, DL has the transformative potential to advance cognitive healthcare, leading to better patient outcomes and driving progress in understanding and treating cognitive disorders. The studies that were conducted on different DL algorithms in cognitive healthcare are summarized in Table 4, including outcomes, applications, and weaknesses/strengths.

4.1. Hybrid modeling

The hybridization of DL models is a widely adopted practice to achieve promising and reliable results compared to single-model approaches. This process involves combining two or more models to either complement each other's weaknesses through optimization or to transform and enhance specific stages of data processing for subsequent models. Hybridization can take several forms, such as integrating different DL architectures or merging DL models with traditional shallow algorithms [92]. In the context of AD detection, it has been found that a hybrid cognitive model with selected psychometric variables, can significantly increase prediction accuracy [93]. Additionally, a hybrid prognostic approach involves using unsupervised learning to create cognitive trajectory classes, which are then used in supervised learning methods to identify individuals at high risk of dementia and guide early interventions [94]. Furthermore, a hybrid approach can be highly effective for predicting early AD using MRI data by employing CNNs to extract spatial features and LSTM networks to handle sequential data during training [95].

To analyze sleep by EEG signals, Zhu et al. [96] developed an integrated DL model for automation. Unlike other ML approaches for EEG analysis, they avoided manual feature engineering and complex pipeline design. For capturing temporal dependencies in the EEG signals, they also proposed the orthogonal constrained RNN as a substitute for employing existing modules. The proposed techniques outperformed baseline models with fewer parameters and training epochs. However, the model still faces challenges with EEG data due to abrupt oscillations in the time domain, leading to fluctuations in accuracy. To address imbalanced performance across different stages, future work could involve better sensor deployment and improved fusion of multi-channel EEG data using a customized end-to-end mixed model.

By combining an improved version of Empirical Mode Decomposition (EMD) named IMEMD with Convolutional Recurrent Neural Network (CRNN), Sun et al. [97] introduced a Speech Emotion Recognition (SER) framework, called IMEMD-CRNN. The study revealed that the mode mixing issue in EMD negatively impacts the performance of EMD-based SER techniques. To address this, the researchers proposed IMEMD, a disturbance-assisted EMD method capable of determining masking signal parameters according to signal characteristics. They extracted 43-dimensional time-frequency features from the Intrinsic Mode Functions (IMFs) acquired through IMEMD and fed the features into the CRNN for emotion recognition. In addition to using 2D CNN layers to collect nonlinear local temporal and frequency data from emotional speech, the CRNN also used Bidirectional Gated Recurrent Units (BiGRU) layers to understand more about temporal context information. In future, the work can be improved by enhancing the decomposition ability of IMEMD and incorporating optimization algorithms to effectively reduce mode mixing in signals.

Leveraging ensemble learning, Iyer et al. [98] proposed an EEG-based emotion recognition technique. The differential entropy of the EEG signals was initially extracted from various frequency bands. The CNN and LSTM models later took advantage of these properties. Combining components from the CNN and LSTM models created a hybrid model. The hybrid model, LSTM, and CNN were then combined to generate an ensemble model. The output demonstrated that the ensemble model performed better than other models used in this approach, achieving superior classification performance. The proposed ensemble model obtained a remarkable accuracy of 97.16% on the SEED dataset, surpassing the performance of the compared methodologies.

For detecting anomalous raw EEG data, Albaqami et al. [99] presented a model comprising two separate paths: WaveNet–LSTM and LSTM. The model's structure was scalable, leading to reduced computational complexity and shorter training time, representing a remarkable improvement over conventional techniques. By incorporating the WaveNet framework, high-level spatial features were extracted from raw EEG data, while the temporal patterns of these features were filtered using LSTM to enhance context correlation. The model was evaluated on the TUAB EEG dataset, whereas it obtained an accuracy of 88.76%. Additionally, the proposed solution incorporated a data augmentation method called Time Reverse EEG data augmentation to generate additional data for improved performance.

4.2. Multimodal learning

With the widespread adoption of wearable sensors and mobile devices, multimodal wearable intelligence is transforming healthcare from conventional systems into more personalized, patient-centered models. This evolution aligns with the objectives of "Healthcare 4.0," which seeks to make healthcare preventive, precise, predictive, and personalized, with particularly significant implications for elder care. To accurately identify individuals with varying degrees of cognitive function, it is essential to integrate regularly collected clinical data, like demographic information, medical history, cognitive testing, neuroimaging, and functional evaluations [100,101]. However, deploying multimodal wearable intelligence for elderly populations, particularly those with dementia, presents several significant challenges. These include the limited availability of cost-effective wearable sensors, device heterogeneity, and the high demand for interoperability across connected systems [102]. In addition, fundamental challenges related to human factors, intelligent system design, implementation, as well as security, social, and ethical concerns further complicate this landscape.

Kuttala et al. [103] conducted a study to investigate the effects of integrating three levels of CNN features on stress detection models. Electrodermal Activity (EDA) and ECG were used as two physiological signals and multi-level CNN features were included for each signal type to create a hierarchical feature set. To achieve multimodal fusion, they employed the Multimodal Transfer Module (MMTM) on feature sets. To measure their efficiency, the experiments were conducted using raw frequency domain data as well as attributes from specific frequency bands. To compare the model's performance, several arrangements of hierarchical features from low, medium, and high levels were utilized. The proposed technique was assessed on four state-of-the-art datasets (ASCERTAIN, CLAS, MAUS, and WAUC), where it outperformed existing methods on various frequency band characteristics by 1-2%. This research aims to further explore hierarchical feature fusion and investigate various multi-modal fusion strategies applied to hierarchical features.

By analyzing temporal facial features, audio, and transcripts from clinical interview videos, Flores et al. [104] developed AudiFace, a multimodal DL model designed for depression screening. AudiFace leverages pre-trained models, including VGGish for audio, BERT for text, and LSTM for temporal facial features, combining these modalities through a bidirectional LSTM with self-attention and a linear fusion layer for final classification. The model exhibits superior performance compared to existing state-of-the-art methods, achieving the highest F1 scores across thirteen of fifteen datasets, with eye gaze emerging as the most significant facial feature. However, this work faced challenges due to the limited participant pool and the imbalanced distribution of depression cases in the datasets, which impacts the generalizability of the results. Future work aims to gather more comprehensive video datasets, explore the screening potential of videos recorded outside clinical settings, and incorporate advanced transformers into the framework.

To identify MCI and Alzheimer, Simfukwe et al. [105] introduced a method using quantitative EEG Time-Frequency (TF) images obtained from patients in a resting state with closed eyes. The preprocessed TF photos were utilized in a customized MobileNet that had its parameters precisely calibrated. The age feature was added to the retrieved image features before being sent into a feed-forward NN to aid with classification. The study's findings revealed that the model, trained on TF images and age information, could serve as valuable biomarkers in the early prediction of cognitive impairment in clinical settings. The models were tested on a group of 60 subjects (healthy control, MCI, dementia) and demonstrated commendable performance, achieving accuracy, sensitivity, and area under the curve (AUC) values exceeding 80%. However, the model gives two-way classification output, and when they tested three classes, the performance was poor (accuracy below 50%). The primary limitation of this study is the small number of participants, necessitating further research with a larger dataset to enhance the performance of the DL models.

To detect AD progression using longitudinal 3D MRI data combined with demographic and cognitive biomarkers, Rahim et al. [106] introduced a multimodal DL framework. The proposed hybrid framework incorporates a 3D CNN, which is followed by a Bidirectional Recurrent Neural Network (BRNN). The 3D CNN extracts intra-slice features from MRI volumes, whereas the BRNN detects inter-sequence patterns over time to predict AD progression. An innovative explainability approach was introduced to help domain experts understand the model's decisions by highlighting key brain regions linked to AD progression. The framework achieved an accuracy of 96% with 99% precision, 92% recall, and 96% AUC, indicating robust detection capabilities with MRI and demographic data. Despite promising results, the study faced limitations such as small, non-longitudinal datasets, compatibility issues preventing model fine-tuning, and lack of visualization for non-MRI modalities. Future research will address these challenges by integrating multimodal time-series data, employing advanced explainability techniques, and exploring cutting-edge DL architectures and data augmentation methods.

4.3. DL with attention

The attention mechanism simulates how the human brain focuses on specific parts of input data, applying a weighted strategy to prioritize relevant information. These mechanisms, inspired by biological systems, have been widely used in various DL applications to highlight the most informative parts of input data [107]. Self-attention, a variant of attention, generates representations by relating different positions within the same sequence, making it particularly effective for capturing long-range dependencies [108]. In recent advances, residual CNNs integrated with self-attention have been used for AD classification by focusing on relevant regions within gray matter slices [109]. The Pyramid Squeeze Attention (PSA) mechanism is notable for its ability to manage spatial information across multi-scale feature maps and establish long-term dependencies between different attention channels [110].

For stress classification, Zulqarnain et al. [111] proposed a DL model. The approach, called Enhanced LSTM (E-LSTM), incorporates a feature attention technique to effectively determine and categorize stress polarity through sequential modeling and capturing word features. By integrating pre-feature attention into E-LSTM, the model effectively captured intricated relationships and extracted keywords using an attention layer in order to classify stress. The accuracy and F1 score of the suggested E-LSTM were 75.54% and 74.58%, respectively. However, when compared to traditional LSTM, E-LSTM had an increased internal complexity due to a greater number of parameters, resulting in longer execution times and higher resource requirements.

To classify subjects at risk for AD using resting-state EEG signals, Sibilano et al. [112] introduced a transformer-based DL model. The dataset included recordings from 17 healthy controls (HCs), 56 subjects with subjective cognitive decline (SCD), and 45 with MCI. The EEG signals were preprocessed and segmented into five frequency bands: delta, theta, alpha, beta, and delta-to-theta. The model, employing multi-head attention to highlight relevant segments of the signal, was trained and validated with a leave-one-subject-out cross-validation method. It achieved the best performance for distinguishing SCD from MCI using the delta band (AUC of 0.807) and for classifying HC, SCD, and MCI using the alpha and theta bands (micro-AUC > 0.74). The study demonstrates that DL methods can effectively utilize non-invasive EEG techniques for stratifying patients at risk for AD, leveraging attention mechanisms to capture temporal dependencies and discriminative patterns. Future improvements include incorporating spatial attention modules, refining signal processing methods, and expanding the subject cohort for better generalization.

Sadiq et al. [113] developed a novel attention-based DL model designed to detect Freezing of Gait (FoG) and Parkinson's disease, as well as to measure the intensity of this disease on the United Parkinson's Disease Rating Scale (UPDRS). The model integrates a CNN for feature extraction, an LSTM for sequence processing, and an attention-based layer for enhanced performance, minimizing the need for extensive data pre-processing. Utilizing the UCF Daphnet dataset and the PhysioNet Gait in Parkinson's disease dataset, the model achieved impressive accuracy rates of 98.74% for FoG detection, 98.72% for disease detection, and 98.05% for assessing its intensity. This end-to-end system offers a non-invasive solution for clinical settings, showing significant improvements over existing models and highlighting the efficacy of attention mechanisms in time series analysis for detecting neurodegenerative diseases. However, the study notes the importance of larger datasets for further validation and model generalization.

Incorporating both CNN and swin-transformer techniques, Xin et al. [114] proposed the Efficient Conv-Swin Net (ECSnet), an innovative approach for automatic AD diagnosis. To effectively encode 3D data into 2D feature maps, the ECSnet model employed a 2.5D-subject technique and a two-stream architecture. Additionally, to improve the model's capacity to generalize, convolution blocks were strategically integrated into the initial stages of the transformer-based network. To further optimize the model, several lightweight approaches were implemented to reduce its parameters and computational complexity, resulting in efficient training and inference. The performance of ECSnet was evaluated on the AIBL dataset, achieving impressive results with a balance accuracy of 92.8% and sensitivity of 91.1%, surpassing previous works. Remarkably, despite solely utilizing 2D algorithms, ECSnet's performance closely rivals that of previous 3D methods. Yet, this model is limited by the exclusion of genetic, biomarker, and certain imaging data due to their limited availability, which restricts the use of multi-modal DL techniques.

4.4. Deep feature learning

DNNs, such as CNNs and RNNs, are instrumental in predicting cognitive decline associated with neurodegenerative diseases [2]. In AD diagnosis, neuroimages are often transformed into 2D slices to leverage pre-trained 2D CNN architectures effectively. Various studies have explored different slicing strategies, including using central slices from multiple planes, selecting the most informative slices based on specific criteria, or treating 2D slices as distinct instances in a multi-instance learning approach [115,116]. RNNs offer valuable advantages by processing sequential data, which enhances the understanding of inter-slice relationships when 3D neuroimage volumes are converted into 2D slices. Different input types are utilized for AD diagnosis, including 1D numerical volumetric features, 2D slices, 3D patches, and whole volumes [108]. Combining CNNs and RNNs can maximize the benefits of both convolution operations and sequential data processing [117].

To identify the stress levels of working pregnant mothers, Sharma et al. [118] used a DL model called Deep Recurrent Neural Network (DRNN) in their study. This model comprised several stacked hidden states of RNN, when compared to traditional LSTM and RNN techniques, enhances computational efficiency while maintaining higher accuracy. The proposed DRNN model attained an accuracy of over 96.00%. The most effective features for categorization were identified to improve prediction accuracy. The DRNN model exhibited reduced training time in comparison to existing methods. Further research can expand real-time applications and improve system accuracy to predict stress levels in pregnant working women and provide societal benefits.

To improve EEG signal classification for schizophrenia diagnosis, Garip et al. [119] introduced a novel hybrid algorithm that enhances the Marine Predator Algorithm (MPA) through chaotic maps. The proposed Chaotic-based Marine Predator Algorithm (CMPA), specifically the Sine Chaotic-based Marine Predator Algorithm (SCMPA), optimizes feature selection by reducing model complexity and selecting the most relevant features. The SCMPA outperforms other chaotic-based MPAs in terms of classification accuracy, as demonstrated with a dataset of 14 subjects. The SCMPA algorithm effectively improves feature representation and classification stability in DT, RF, and extra tree methods. However, SCMPA is limited to single-objective continuous optimization problems, and future research should focus on extending its capabilities to binary, multi-objective, and discrete optimization scenarios.

To minimize dependence on cognitive testing, Ghoraani et al. [120] presented an innovative diagnostic algorithm that utilizes gait analysis and ML to detect MCI and AD. The research involved gait data collection from 78 elderly participants, including healthy, MCI, and AD individuals, performing both single and dual-task walking. By extracting and analyzing 108 gait features, the study identified 25 key features for distinguishing healthy individuals from those with MCI or AD, and 13 features for differentiating MCI from AD. The SVM model achieved an average classification accuracy of 78% in five-fold cross-validation, which is comparable to 83% accuracy using the Montreal Cognitive Assessment (MoCA) score. This approach highlights the potential for gait-based screening to be integrated into clinical settings, offering a practical and objective method for early identification of cognitive decline.

4.5. Adversarial learning

GANs are emerging as powerful tools in neuroimaging, particularly for analyzing neurological conditions such as AD, brain tumors, brain aging and multiple sclerosis. As advanced DL models, GANs excel at capturing complex, subtle disease-related changes in the brain, outperforming traditional generative methods. Accurately modeling healthy brain aging is crucial for establishing baselines to detect pathological changes. GANs can be leveraged to simulate both normal and abnormal brain developments, offering valuable insights into disease progression and prognosis [121,122]. However, applying GANs in neuroimaging presents several challenges, including modeling tumor growth, tracking lesion progression, addressing disease heterogeneity, ensuring model interpretability, handling multi-view learning, and overcoming practical hurdles in clinical deployment [123].

To address key limitations in existing Magnetic Resonance Imaging (MRI) simulators, such as lack of individualization, low resolution, and 2D constraints, Ravi et al. [124] introduced 4D-DANI-Net, a DL framework that generates high-resolution, longitudinal MRI scans for simulating neurodegeneration in aging and dementia. By employing adversarial training with biologically-informed spatiotemporal constraints, 4D-DANI-Net overcomes memory limitations through innovations like Profile Weight Functions (PWFs), 3D super-resolution, and a transfer learning method for personalization. The framework was trained and then tested on a large dataset from the Alzheimer's Disease Neuroimaging Initiative (ADNI), demonstrating superior image quality, accuracy in regional brain volume estimation, and expert assessment compared to benchmark models. The system aims to create a "digital twin" of the brain, potentially revolutionizing clinical trials through virtual placebos and advancing personalized medicine by integrating additional demographic and genetic factors. Future work aims to extend the framework to other medical imaging modalities and conditions.

To predict the progression of AD, Zhao et al. [125] presented a novel framework that generates future brain MRI images and classifies the clinical stage based on these predicted images. The framework has two main components: a 3D multi-information Generative Adversarial Network (mi-GAN) and a 3D multi-class DenseNet-based model. The mi-GAN is designed to produce high-quality 3D brain MRI images at future time points (e.g., four years ahead) based on baseline images and additional information. The 3D DenseNet model is then used to classify the clinical stage of these generated images, leveraging a focal loss to optimize performance. Experimental results on the ADNI dataset demonstrated the effectiveness of the framework, attaining a structural similarity index (SSIM) of 0.943 between real and generated images, and a 6.04% improvement in classification accuracy over previous methods. While the framework shows promising results, the authors noted areas for future improvement, particularly in predicting gray matter distribution and short-term brain changes.

To address challenges related to variations in imaging acquisition conditions and limited data availability, Kim et al. [126] developed a GAN-based approach with slice selective learning for classifying AD and Normal Cognition (NC). The model was trained using 18F-fluorodeoxyglucose PET/CT images from the ADNI and tested on an independent dataset from Severance Hospital. The approach utilized a Boundary Equilibrium GAN (BEGAN) for feature extraction and a SVM for classification. The model employed slice selective learning to minimize computational expenses and extract unbiased features, focusing on slices that encompass critical regions of interest. It achieved high accuracy, with rates of 94.33% and 94.82% for the Severance and ADNI datasets, respectively, and demonstrated strong sensitivity and specificity. The experimental results were consistent across both datasets, with a statistically significant improvement in performance when using double slices compared to single slices. However, the study highlights the need for further validation with additional independent datasets and the exploration of other imaging planes, such as axial and sagittal.

4.6. Explainable learning

Explainability has already been applied in healthcare and medicine in various ways. AI has significantly advanced medical image analysis, and researchers are now working to combine these high-accuracy models with enhanced explainability and interpretability [127]. A clinician-facing explanation interface, such as a dashboard can utilize sensor data from smart homes to monitor cognitive decline in the elderly and promptly alert healthcare providers [128]. In fields like mental health and psychiatry, the need for explainability is even more critical due to the probabilistic relationships between data describing disorders, symptoms, syndromes, and outcomes. The Transparency and Interpretability for Understandability (TIFU) framework is designed to improve the understandability of AI models by balancing transparency and interpretability for users [129]. The applications of explainable learning in mental health demand a high degree of understandability, as these clinical contexts are high-stakes, and Artificial Intelligence (AI) tools should support healthcare professionals by simplifying decision-making rather than adding complexity.

Relying on dynamic brain connectivity patterns, Gao et al. [130] introduced an interpretable LSTM model to estimate the progression or improvement of patients with Mild Cognitive Impairment (MCI). Their proposed interpretation method, Transiently-realized Event Classifier Activation Map (TEAM), utilized gradients to explain class-distinguishing features in multivariate time series data derived from the time-attention LSTM classifier. TEAM provided insights into the relevant aspects of the data that contribute to classification decisions. TEAM interpreted class difference features with 100% sensitivity and 98.13% mean specificity, achieving significant results. Nevertheless, the study is constrained by a small sample size of fewer than 100 subjects from the OASIS-3 dataset, which may limit the generalizability of the results. Additionally, the research lacks consideration of lifestyle factors and other diverse influences, focusing primarily on neuroimaging data. Interpreting the results on different datasets is crucial to ensure the reproducibility of biomarkers, including shared group dynamic biomarkers, and to identify potential interpretation biases.

Studying the network structure and dynamical characteristics of patients with AD, Li et al. [131] looked for changes in the cortical rhythm. Both AD patients and health controls have their biological data analyzed, with a focus on the energy characteristics of EEG signal sub-bands. Notably, distinctive rhythm patterns were observed in AD patients, especially in the theta and alpha bands. To delve deeper into rhythm dynamics, the researchers utilized a RNN to study how neural states undergo formation and transformation. The findings revealed a significant decrease in neural coupling strength during the AD state, impacting the transmission of information. By analyzing cortical rhythm transitions and low-dimensional trajectories, the study identified slower updates and higher communication costs in AD, thus explaining abnormal brain network synchronization. They used LIF neurons to build RNNs. However, it is also essential to note that LIF neurons, being continuous-time models triggered by a predefined threshold for spike firing, do not correctly capture the principal biological features of neurons.

To improve the monitoring of cognitively impaired individuals in smart homes, Javed et al. [132] introduced XAI-HAR, a new approach for Human Activity Recognition (HAR) enhanced by Explainable Artificial Intelligence (XAI). XAI-HAR identifies key features from sensor data using physical key feature selection (PKFS) and statistical key feature selection (SKFS), aiming to handle outliers and class variance. The system employs ML models, including Naive Bayes (NB), RF, KNN, SVM, DT, and DL models such as DNN, CNN, and CNN-based LSTM (CNN-LSTM). The RF classifier, coupled with Local Interpretable Model Agnostic (LIME) for explainability, outperforms other models, achieving an F-score of 96% for health and dementia classification, and 95-97% for HAR in dementia and healthy individuals. Future work aims to test XAI-HAR with more complex datasets, including those involving pets, and to extend its application to other cognitive conditions like Parkinson's disease and AD.

4.7. Federated learning

Federated learning (FL) has emerged as a promising solution for training DL models on decentralized healthcare data from wearable devices, enabling privacy-preserving smart healthcare applications. However, there are still relatively few studies that explore the potential of FL in cognitive healthcare [133]. Edge of Things (EoT) offers an opportunity to further develop FL frameworks by integrating cloud computing with healthcare systems, allowing data to be transmitted more efficiently while maintaining privacy [134]. Additionally, the Internet of Medical Things (IoMT) can enhance service quality for patients, clinicians, and medical professionals by increasing the flexibility, interoperability, and connectivity of smart devices through advanced wireless technologies [135]. These devices can monitor body parameters in real-time and transmit the data to a decision support system for further processing. This approach enables autonomous systems, minimizing the need for human intervention and enhancing healthcare efficiency [35].

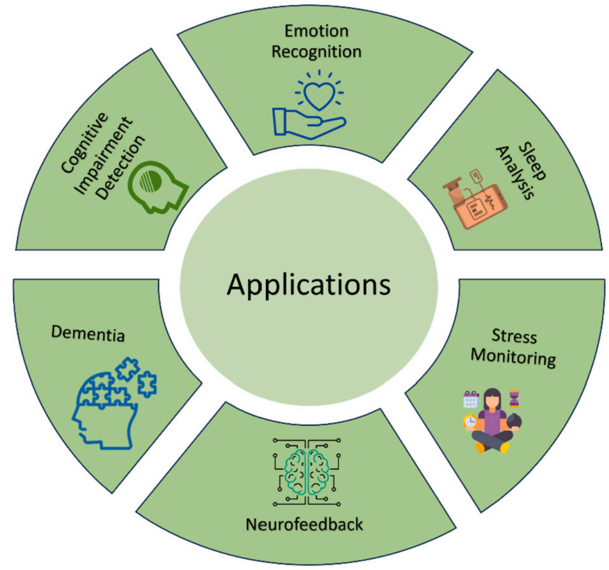

Fig. 2. Applications of DL in cognitive healthcare.

5. Applications of DL in cognitive healthcare

In the last decade, healthcare has witnessed an unprecedented transformation through integrated advanced technologies. Among these technologies, DL has transpired as a powerful tool, revolutionizing the landscape of cognitive healthcare. It has found remarkable applications in the cognitive healthcare realm, encompassing numerous conditions affecting psychological functions, such as neurological disorders, mental health conditions, and cognitive impairments. By leveraging DL techniques, healthcare professionals and researchers are gaining novel insights, developing predictive models, and enhancing diagnostic accuracy, thereby ushering in a new era of personalized and data-driven cognitive healthcare interventions [136–138]. This section of the paper delves into the diverse applications of DL in cognitive impairment and emotion recognition, stress monitoring, sleep analysis, and neurofeedback (Fig. 2).

5.1. Cognitive impairment detection

The timely diagnosis of MCI enhances therapeutic interventions and substantially postpones disease advancement, yielding societal and economic advantages. MRI, a vital diagnostic tool for MCI, can furnish neuropsychological data for scrutinizing disparities in brain anatomy and activity. MCI is categorized into early (EMCI) and late (LMCI) stages even though distinguishing between healthy individuals and MCI patients, particularly in the EMCI phase, is challenging due to analogous brain structures. To address this, Gorji et al. [139] employed DL to differentiate healthy subjects from EMCI and LMCI patients via MRI findings. The study adeptly extracted valuable attributes from MRIs by applying a proficient CNN architecture, classifying the subjects into healthy, LMCI, or EMCI. The research cohort encompassed MRIs from six hundred participants, comprising 200 from each group. Model training has 70% of the dataset, with the remaining 30% reserved for testing. The

Table 4
Overview of DL techniques in cognitive healthcare.

Method	Application	Objective	Outcome	Remarks	Ref.
Hybrid Modeling	Sleep analysis	Automated sleep analysis using EEG signals.	Outperformed baseline models with fewer parameters and training epochs.	Faces challenges with EEG data due to abrupt oscillations in the time domain, leading to fluctuations in accuracy.	[96]
	Speech emotion recognition	To address the mode mixing issue in EMD that negatively impacts the performance of SER techniques.	Used BiGRU layers to understand more about temporal context information and achieved promising results.	Recommends enhancing this work by incorporating optimization algorithms to effectively reduce mode mixing in signals.	[97]
	Emotion recognition	To develop an EEG-based emotion recognition technique using ensemble learning.	Obtained an impressive accuracy of 97.16% on the SEED dataset.	Demonstrated that the ensemble model performed better than other models used in the proposed approach.	[98]
	EEG anomaly detection	To develop automatic detection of abnormal raw EEG data.	Acquired an accuracy of 88.76% on the TUAB EEG dataset.	Incorporated a data augmentation method to generate additional data for improved performance.	[99]
Multimodal Learning	Stress detection	To investigate the impact of combining different levels of CNN features for stress detection.	Outperformed existing stress detection models by 1 to 2% on frequency band features.	Aims to explore hierarchical feature fusion and investigate various multi-modal fusion techniques applied to hierarchical features.	[103]
	Depression screening	To analyze temporal facial features, audio, and transcripts from clinical interview videos for depression assessment.	Achieved the highest F1 scores across thirteen of fifteen datasets.	Faces challenges due to the limited number of participants and the unequal distribution of depression cases in the datasets.	[104]
	Identifying MCI and AD patients	To classify individuals with MCI and AD from healthy controls.	Demonstrated commendable performance, achieving accuracy, sensitivity, and AUC values exceeding 80%.	Provides two-way classification output, but performance drops significantly (accuracy below 50%) when tested with three classes.	[105]
	AD progression	To detect AD progression and help domain experts understand the model's decisions.	Achieved 96% accuracy, 99% precision, 92% recall, and 96% AUC.	Possesses limitations, including small, non-longitudinal datasets, compatibility issues, and a lack of visualization for non-MRI modalities.	[106]
DL with Attention	Stress classification	To effectively determine and categorize stress polarity through sequential modeling and word-feature capturing.	Attained an accuracy of 75.54% and an F1 score of 74.58%.	Exhibits internal complexity due to a higher number of parameters, leading to longer execution times and increased resource requirements.	[111]
	Risk stratification for AD	To classify subjects at risk for AD based on resting-state EEG signals.	Achieved the best performance for distinguishing SCD from MCI using the delta band and for classifying HC, SCD, and MCI using the alpha and theta bands.	Recommends using spatial attention modules, refining signal processing, and expanding the subject cohort for improved generalization.	[112]
	Neurodegenerative diseases	To detect FoG and Parkinson's disease, as well as to measure the intensity of this disease on the UPDRS.	Attained impressive accuracy rates of 98.74% for FoG detection, 98.72% for disease detection, and 98.05% for measuring its intensity.	Highlights the efficacy of attention mechanisms in time series analysis for detecting neurodegenerative diseases.	[113]
	AD diagnosis	To effectively encode 3D data into 2D feature maps.	Recorded impressive results with a balance accuracy of 92.8% and sensitivity of 91.1% on the AIBL dataset.	Performs similarly to previous 3D methods despite using only 2D algorithms.	[114]
Deep Feature Learning	Stress detection	To predict stress levels in working pregnant women.	Achieved an accuracy of over 96.00%.	Reduces training time in comparison to existing methods.	[118]
	Schizophrenia diagnosis	Improving EEG signal classification for identifying schizophrenia patients.	Outperformed other chaotic-based MPAs, as shown in a study with 14 subjects.	Improves feature representation and classification stability in tree methods, but is limited to single-objective continuous optimization problems.	[119]
	AD and MCI detection	Using gait analysis and ML to reduce reliance on cognitive testing.	Achieved an average classification accuracy of 78% with SVM model.	Highlights the potential for gait-based screening to be integrated into clinical settings for early detection of cognitive decline.	[120]
Adversarial Learning	Neurodegeneration simulation	To address key limitations in existing MRI simulators.	Demonstrated superior image quality, accuracy in regional brain volume estimation, and expert assessment compared to benchmark models.	Aims to develop a brain's "digital twin" to transform clinical trials and advance personalized medicine.	[124]
	AD progression	To generate future brain MRI images and classify the clinical stage of them.	Obtained a structural similarity index (SSIM) of 0.943 between real and generated images, and a 6.04% improvement in classification accuracy over previous methods.	Shows promising results but highlights the need for improvements in predicting gray matter distribution and short-term brain changes.	[125]
	Classifying AD and NC subjects	To address challenges related to variations in imaging acquisition conditions and limited data availability.	Achieved 94.33% and 94.82% accuracy rates for the Severance and ADNI datasets, respectively, with strong sensitivity and specificity.	Performance significantly improves with double slices over single slices.	[126]
Explainable Learning	MCI progression	Developing an interpretable model to estimate the progression of patients with MCI.	Interpreted class difference features with 100% sensitivity and 98.13% mean specificity.	Emphasizes the importance for interpreting results across various datasets to ensure the reproducibility of biomarkers, while also identifying potential interpretation biases.	[130]
	Understanding AD dynamics	To study how alterations in network architecture and dynamic features influence abnormal changes in cortical rhythm.	Identified distinctive rhythm patterns in AD patients, specifically in the theta and alpha bands.	Utilizes LIF neurons which do not accurately replicate the essential biological features of neurons.	[131]
	HAR	To improve the monitoring of cognitively impaired individuals in smart homes.	Achieved 96% F-score for health and dementia classification, and 95-97% for activity recognition in dementia and healthy individuals.	Aims to test the approach with more complex datasets and extend its application to other cognitive conditions.	[132]

outcomes demonstrated the highest accuracy (94.54%) in distinguishing between LMCI and NC classes when considering the sagittal plane view. However, the model's generalizability to novel datasets and disparate imaging centers was not evaluated to validate the robustness and dependability in diverse scenarios.

Due to the heterogeneous nature of MCI etiology, cognitive decline rates vary among patients, and some do not progress to AD [140]. Identifying treatable MCI patients is crucial, but current visual analysis lacks objectivity, while quantitative methods require complex processing [141–144]. Choi et al. [145] aimed to create an automated system grounded on deep CNNs to predict cognitive decline in MCI using fluorodeoxyglucose and florbetapir PET scans. PET images from 183 normal, 139 AD, and 171 MCI subjects were sourced from the ADNI. The CNN, trained on 3D PET volumes from AD and controls, outperformed conventional quantification in predicting MCI-to-AD conversion (84.2% accuracy). The predictive performance of CNN significantly surpassed available quantification methods ($p < 0.05$) fixed on Receiver Operator Characteristic (ROC) curve analysis. Network output scores correlated strongly with cognitive changes ($p < 0.05$). These findings demonstrate DL's practicality for predictive neuroimaging biomarkers. Further, it may entail independent large-cohort clinical trial validation.

The urgent requirement for accurate, cost-effective, and user-friendly methods to detect dementia is evident. In a study [146], a dataset of 1264 voice recordings was exerted, comprising 483 from individuals with NC, 451 from those with MCI, and 330 from dementia participants. They fabricated two DL models: a two-level LSTM and a CNN. These models aimed to classify recordings and differentiate between NC and dementia. Through meticulous 5-fold cross-validation, the CNN model achieved a mean AUC of 0.805 ± 0.027 for classification accuracy, while the LSTM model exhibited a mean AUC of 0.740 ± 0.017. Nevertheless, it's important to note that these models were devised using voice recordings from the FHS dataset, representing a population group from the New England area of the United States. Although robust cross-validation highlighted consistent performance, external validation across diverse cohorts remains essential to confirm their applicability across broader contexts.

Focusing on EEG for the diagnosis of MCI, another study [147] indicated the inadequacies of shallow ML approaches for extracting the underlying structure of the data for useful biomarkers. The authors introduced a DL scheme featuring a GRU model to differentiate between MCI patients and healthy controls employing EEG data. The four vital phases include collecting raw EEG data, preprocessing, extracting hidden features, classifying the subjects, and evaluating function. Recorded EEG signals from 27 samples were processed and fed into 4 classifiers: KNN, SVM, LSTM and GRU. The proposed approach secured a peak accuracy of 96.91% while maintaining the lowest false alarm rate (4.11%), with framework stability estimated by applying 5-fold cross-validation. The proposed GRU-based model aids as a dependable biomarker, facilitating the development of an automated MCI detection approach. However, utilizing CNNs for AD diagnosis remains challenging due to limited imaging data availability, potentially leading to the loss of 3D spatial information when using flattening layers. To address this, Feng et al. [148] proposed an innovative DL framework integrating 3D CNN with fully stacked bidirectional long short-term memory (FSBi-LSTM) to enhance AD diagnosis efficiency using MRI and PET. The approach achieved notable accuracy rates on the ADNI dataset, with 94.82%, 86.36%, and 65.35% for discerning Alzheimer, progressive MCI (pMCI), and stable MCI (sMCI) from NC, respectively, surpassing existing methods. Notably, this method obviates the need for manual feature extraction, avoiding subjectivity. Nonetheless, drawbacks include the difficulty of diagnosing subtle sMCI due to anatomical changes and the absence of direct brain lesion structure detection. Furthermore, longitudinal MRI data and overcoming the cascade of CNN and LSTM for lesion structure identification are not incorporated, which could offer supplementary insights into disease progression.

5.2. Emotion recognition

The evolving landscape of NNs and the growing call for real-time and unerring SER within human-computer interactions necessitate a comprehensive evaluation of methods and databases. Abbaschian et al. [149] conducted a review of DL and conventional ML techniques for SER, comparing them with available datasets to provide practical insights. Additionally, a multi-faceted assessment of NN approaches is advocated. Recent databases offer larger data pools, with an average sample duration of 2.8 seconds; notably, Toronto Emotional Speech Set (TESS) deviates as an outlier with a 2.1 second average. Although TESS has been utilized recently for automatic speech-emotion detection, it is earmarked for future research due to its challenging nature with shorter emotional speech utterances. Subsequent investigations could focus on robust and dataset-agnostic solutions, facilitating the deployment of models in real-world scenarios.

In comprehending intricate human behavior, studying physical traits across various modalities—facial, physical gestures, and vocal are pivotal. Spontaneous multi-modal emotion recognition, a prominent area in human behavior analysis, has garnered substantial attention. Schoneveld et al. [150] introduced a novel DL method for audio-visual emotion recognition. The proposed method exploits the latest advancements, such as knowledge filtration and high-performance architectures in the DL field. It merges feature representations from visual and audio modalities through fusion on the model-level. A RNN captures temporal dynamics. The proposed approach demonstrates significant performance superiority over existing methodologies in valence prediction on the RECOLA dataset. Additionally, their visual feature extraction network exceeds state-of-the-art results on Google Facial Expression Comparison (FEC) and AffectNet datasets. Although their one-million-image unlabeled dataset is twice the combined size of AffectNet and Google FEC's face count, further exploration is needed to determine how well the benefits of ImageNet's unlabeled data transfer to facial expression analysis. In forthcoming research, optimal strategies for continuous emotion encoding, label distribution learning, or ranking can be investigated.

Emotional responses in EEG signals are individualized, varying across people due to distinct reactions to the same stimuli. However, subject-independent emotion recognition holds significance, especially in scenarios like emotion detection from paralyzed or injured faces, where pre-incident EEG data is absent for model training. Pandey et al. [151] prompted the identification of shared EEG patterns corresponding to emotions across subjects. The authors suggested a subject-independent emotion recognition process using Variational Mode Decomposition (VMD) for feature distillation and a DNN for classification. The approach is assessed on the DEAP dataset, revealing that VMD-based features from the top 3 IMFs surpass EMD-based features. DNN outperforms SVM classifiers in subject-independent emotion recognition. Crucially, this generalized method employs distinct EEG data for model training and testing, enabling emotion recognition for any individual not involved in the classifier's training.

Emotions stem from the central and peripheral nervous systems, making EEG signals a fitting medium to characterize them due to their direct reflection of human emotional states. Sharma et al. [152] outlined an automated approach employing nonlinear statistics (higher-order) and DL algorithms to classify emotions-labeled EEG signals. The signal was decomposed into sub-bands using the discrete wavelet transform. The Third-order Cumulants (ToC) unveil nonlinear dynamics in each sub-band, resulting in higher-dimensional data rich in replicated and superfluous information due to symmetries. Particle swarm optimization, a data reduction method, is adopted to eliminate irrelevant data. They utilized LSTM techniques to extract emotion variation from the processed data associated with labeled EEG signals. The research utilized the DEAP dataset, yielding an average 82.01% accuracy using a 10-fold cross-validation approach for four-labeled emotion categories. The algorithm's assessment of ToC across a large dataset, with deep algorithm parameter constraints, marginally influenced processing speed.

5.3. Sleep analysis

Sleep disturbances are prevalent in various neurological disorders and can significantly impact daily life. While conventional methods for sleep stage monitoring involve laborious manual estimation of Polysomnogram (PSG) signals collected in controlled environments, automated techniques hold the potential for accurate neurological disorder detection. A versatile DL approach utilizing raw PSG signals, and employing a One-dimensional CNN (1D-CNN) was developed by Yildirim et al. [153]. This approach analyzes Electrooculogram (EOG) and EEG data for sleep stage categorization. The proposed model's effectiveness is estimated using publicly available sleep databases (sleep-edf and edfx). It achieved the highest accuracy rates across 2-6 sleep classes in the datasets. Although the model holds promise for clinical implementation, the evaluation has focused on signal-level criteria. It might have applied on extensive PSG datasets and analyzed patient-level. Exploring alternative DL strategies, such as combining CNN and LSTM, could enhance recognition performance.

EEG is a foundational signal for brain activity monitoring and sleep disorder diagnosis. Manual sleep stage scoring by experts is tedious and restrained by reliability inconsistencies. Addressing this, Mousavi et al. [154] introduced SleepEEGNet, an automatic sleep stage notation procedure employing a single-channel EEG signal. Comprising deep CNNs for frequency information, time-invariant feature extraction, and a sequence-to-sequence model to entrap intricate long-term dependencies, SleepEEGNet deploys novel loss functions to mitigate class imbalance issues in sleep datasets during training. Evaluation reveals superior annotation performance, achieving 84.26% overall accuracy. However, similar to other DL methods, ample sleep stage samples are required for discriminative feature learning in training. As a sequence-to-sequence model, sufficient 30-second EEG epochs per time step are needed for scoring input. Moreover, the assessment is conducted with two EEG channels from the Physionet Sleep-EDF dataset, necessitating model adaptation for new channels to assess performance. Further, Eldele et al. [155] introduced AttnSleep, an attention-based deep structure that employs single-channel EEG signals to allocate sleep phases. It featured a Multi-resolution Convolutional Neural Network (MRCNN) and Adaptive Feature Recalibration (AFR) for enhanced feature extraction. MRCNN captures frequency (high and low) features, while AFR refines features' quality by modeling inter-dependencies. Another component, the temporal context encoder utilized a multi-head attention system and intermittent convolutions to encapsulate temporal relationships within the features. Performance assessment on three public datasets demonstrated the stability of AttnSleep across different numbers of heads. Nonetheless, domain adaptation techniques could be explored to adjust the model trained on labeled data for classifying unlabeled sleep data from other datasets, ensuring generalizability.

Polysomnography is the benchmark for sleep apnea diagnosis, involving an overnight recording of physiological signals: EEG, ECG, EMG, EOG, respiratory effort, oxygen saturation in arterial blood, body position, and airflow. While effective, PSG is resource-intensive, requiring reliable sleep disorder diagnostic alternatives with fewer signals. Notably, OSA patients face heightened cardiovascular risks during sleep. Dey et al. [156] pointed to enhancing diagnostic accuracy solely using single-channel ECG recordings through a DL approach employing CNN. The proposed system analyzes single-lead ECG signals to detect OSA. This method combines feature learning with supervised classification, demonstrating a significant average accuracy improvement of over 9% compared to existing literature. Although computationally demanding, the scheme's long signal records and offline expert observation render its computational load manageable. Nonetheless, the complexity doesn't preclude deploying the algorithm on a microcontroller, as ARM-based microcontrollers have already demonstrated the implementation of such systems.

5.4. Stress monitoring

The influence of external forces on the human body, leading to the body's response, is a recognized factor. This body response to external forces is known as stress [157,158]. Stressful conditions trigger a range of psychological and physiological processes. In a research by Masood et al. [159], physiological stress monitoring criteria prioritized comfort and non-disruption of regular work. Included were disparity measurements of heart rate, electro-dermal response or changes in the skin, and respiration patterns while disregarding variables such as pupil dilation or gesture recognition that disrupt regular activities. Stress severity was modeled using a DL scheme for psychological stress assessment. A wireless network sensor captured physiological signals and breathing pattern deviation activated under tough laboratory conditions. Protocols engaged participants in cognitive tasks of varying difficulty levels, and evoking different stress levels. Deep breathing techniques were employed as both pre-activity and post-activity to alleviate stress. Neural signals were extracted alongside conventional physiological signals. A CNN framework aided in identifying stressed activities and their severity through training and validating input datasets. In particular, neural signals significantly enhanced the classification model's efficiency in assessing mental stress. Despite a moderate participant count, future research should involve more participants, and real-world stress scenarios could be added alongside laboratory experiments.

By utilizing multimodal data collected from motion and wearable sensors to avert individuals from numerous stress-related health issue, Bobade et al. [160] introduced a diverse DL technique for stress recognition. The dataset encompasses sensor modalities like electrocardiogram, respiration, blood volume pulse, electro-dermal activity, electromyogram, three-axis acceleration, and body temperature across three physiological states: amusement, stress, and neutral. Extracted from the WESAD dataset, they introduced a feedforward Artificial Neural Network (ANN) for classification tasks. The results demonstrated accuracies up to 84.32% and 95.21% using DL for three-class and binary classification, respectively. Future work could incorporate self-reported data from the subjects obtained through organized questionnaires, and amalgamate various modalities such as audio/video recordings, facial cues, and FITBIT data to form a comprehensive dataset, enhancing stress detection accuracy. Continual exposure to high stress can significantly impact work and studies, potentially leading to cancer and cardiovascular disease. Thus, effective stress tracking and management are crucial to mitigate adverse aftermath from intemperate psychological stress. Traditional methods involve extracting RR interval characteristics from ECG signals in frequency domains, followed by ML classifiers such as DT, RF, and SVM for stress stage classification. However, they require at least sixty seconds of ECG data and other signals for high accuracy, hampering real-time applicability. To address this, Zhang et al. [161] devised a framework using BiLSTM and CNN. It achieved up to 0.865 accuracy across 3 stress levels using a ten-second ECG signal, outperforming conventional methods by 0.228. It makes this framework better suited for real-time applications. Nevertheless, personality differences were not considered during development, which might have a substantial impact on performance improvement.

To precisely identify work-related stress, Seo et al. [162] developed a DL approach that leverages multimodal signals. A protocol simulating stressful situations was designed, involving 24 subjects, from whom respiration, ECG, and video data were collected. The signals were preprocessed, and 10-second ECG and respiration signals, along with facial feature sequences, were fed into a DNN. Sixty-eight facial landmarks and facial textures were extracted for analysis. Data fusion was applied at two levels, namely feature-level and decision-level. In two-level stress classification, feature-level fusion of respiration and facial landmarks attained 73.3% accuracy (F1 score: 0.700 and AUC: 0.822), while combining ECG, respiration, and facial landmarks yielded 54.4% accuracy (F1 score: 0.508 and AUC: 0.727) in three-level classification. Decision-level fusion revealed that the significance of each signal varied depending on the stress classification task. Overlapping samples between classes contributed to performance degradation. The findings of the research suggest that the proposed method can enhance stress detection by integrating multimodal signals.

5.5. Neurofeedback

Neurofeedback training has shown promise in treating chronic pains, such as Central Neuropathic Pain (CNP), utilizing the brain's self-regulation capabilities. Saif et al. [163] presented a study that reports on the performance of a Brain-Computer Interface (BCI) relying on DL features to evaluate the outcomes of neurofeedback training for addressing CNP in paraplegic patients. The study utilizes Motor-Imagery Electroencephalography (MI-EEG) data gathered from three distinct groups: able-bodied participants, paraplegic patients with CNP, and paraplegic patients without CNP. DL features are extracted from the MI-EEG using ResNet50 network, followed by classification via a SVM-based BCI. After developing the SVM-based BCI, new MI-EEG samples from paraplegic patients undergoing neurofeedback sessions have been employed for performance assessment. Findings indicate that the BCI's prediction accuracy varies with the MI task, participant groups, and EEG channel combinations. The BCI achieved its highest efficiency, with an accuracy of 99.94 $\pm$ 0.05%, using foot MI-EEG, comparing able-bodied and paraplegic groups and focusing on the C4 electrode over the sensorimotor cortex. This study's findings not only offer important implications for increasing the efficiency of MI-EEG-based BCIs, but also open avenues for future research in this domain.

Motor symptoms linked to Parkinson's disease are associated with abnormal increases in beta-oscillations within the basal ganglia. While medical care such as medication and Deep Brain Stimulation (DBS) alleviate these oscillations and enhance motor function, Bichsel et al. [164] investigated the potential of neurofeedback as an intrinsic modulation approach. They employed pathological beta oscillation's real-time processing in the subthalamic region using implanted DBS electrodes to deliver deep electrical neurofeedback. The study comprised pre-neurofeedback, neurofeedback, and transfer phases. Patients swiftly learned to control beta-oscillatory activity through visual neurofeedback, leading to enhanced motor performance due to reduced activity during an one-hour training session. The acquired strategies for endogenous control persisted even after removing visual neurofeedback, indicating short-term retention. Besides, applying the learned mental strategies two days later without neurofeedback yet resulted in motor improvement. This intracranial electrophysiological human study substantiates a significant breakthrough by presenting the initial empirical proof of patients expeditiously acquiring real-time volitional regulation over ongoing deep-brain oscillatory activity through the implementation of visual neurofeedback. This study marks a pioneering advancement in the realm of intracranial electrophysiological research. Even so, the complete scope of voluntary self-control of deep brain oscillatory activity and its impact on motor outcomes require further exploration, as this study was constrained by a brief intervention period.

The significance of hyperparameter optimization has been overlooked in DL related to EEG research, leaving the extent of its impact erratic. To enhance imagined speech EEG classification using DL methods, Cooney et al. [165] investigated the influence of hyperparameter optimization on classifier performance through statistical analysis. Three different CNNs were trained on imagined speech EEG incorporating nested cross-validation for optimizing hyperparameters. These networks were independently implemented for EEG decoding, utilizing a dataset that included both words and vowels. CNN outcomes were contrasted to three benchmark ML methods: RF, SVM, and regularized Linear Discriminant Analysis. Statistical evaluation was conducted for intra-subject and inter-subject hyperparameter optimization methods. CNN exhibited notably superior accuracy compared to standard techniques when trained on the datasets. The statistical analysis highlighted the significance of varying hyperparameter values and their interaction with CNNs. The findings of hyperparameter optimization underscore its critical role in training CNNs for imagined speech decoding. However, the performance differences among the 3 CNNs were insignificant, as well as the influences of intra-subject and inter-subject optimization methods were also minor.

The current achievements of deep algorithms in effectively categorizing diverse brain signals have led to a growing interest in exploring their applicability for decoding Motor Imagery (MI) signals across different individuals in real-time with contingent neurofeedback. It is a crucial aspect of BCI development aimed at neurorehabilitation. In a recent study [166], the persistent challenge of creating a calibration-free and continuously decodable MI-BCI is tackled using a novel CNN-based learning process. They introduced the innovative concept of Mega Blocks, which are the architectural elements that can be flexibly repeated within the network to accommodate variations between subjects. These blocks are optimized through Bayesian hyperparameter optimization and are designed to facilitate inter-subject continual decoding of MI related EEG signals. The findings derived from the BCI competition exhibit average decoding accuracies of 71.49% and 70.84% using Adaptive Moment Estimation (Adam) and Stochastic Gradient Descent (SGDM) training techniques, encompassing 7 of 9 subjects. This research pioneers the viability of leveraging CNN architectures for inter-subject continuous decoding, paving the way for calibration-free MI-BCIs fabrication that is pragmatic for real-world implementations. In this context, the reduction of calibration requirements and the seamless provision of ongoing feedback are pivotal in enriching the user experience, consequently amplifying the potential for effective neurorehabilitation outcomes.

The integration of DL techniques into cognitive healthcare holds immense promise for advancing our understanding of psychological affliction and enhancing patient care. From aiding in accurate diagnosis to enabling personalized treatment strategies, DL's ability to extract meaningful patterns from complex datasets marks a significant innovation in the field. It stands poised to significantly improve the lives of individuals, offering new avenues of hope and progress for both patients and the medical community. Table 5 presents the studies on the applications of DL models in several cognitive healthcare applications, including outcomes and strengths/weaknesses.

6. Challenges, and benefits of DL in cognitive healthcare

With the emergence of DL, the sector of cognitive healthcare is experiencing a rapid transformation, offering both remarkable benefits and significant challenges. As DL algorithms have become proficient in learning complex relationships and extracting meaningful insights from cognitive health data, they can assist in an improved diagnosis, personalized treatment, early intervention and remote monitoring. However, these possibilities also raise critical concerns related to data privacy and security, data quality and accessibility, interpretability and explainability, generalization and transferability, and ethical considerations. By addressing these challenges, future research in cognitive healthcare should focus on leveraging the potential of DL in terms of multimodal signal analysis, transfer learning, explainable AI, personalized care and real-world clinical validation and adoption.

6.1. Benefits

Despite the challenges that need to be addressed prior to the implementation of DL in cognitive healthcare settings, there exist a number of potential benefits. These include improved diagnosis, personalized treatments, early intervention, remote monitoring, assistive technologies and reduced healthcare costs.

6.1.1. Improved diagnosis

DL holds the immense potential to significantly impact the field of cognitive healthcare, especially in clinical neurosciences, where it can assist in diagnosing neurologic diseases and analyzing medical images

Table 5
Surveyed studies on the applications of DL techniques in cognitive healthcare.

Applications	Model/ network	Objective	Outcome/accuracy	Remarks	Ref.
Cognitive impairment detection	CNN	To differentiate healthy control from early and late MCI patients using MRI findings.	94.54% accuracy	Model's performance to novel datasets and disparate imaging centers could be assessed to validate generalizability.	[139]
	CNN	Predicting cognitive decline in MCI using fluorodeoxyglucose and florbetapir PET scans.	Achieved 84.2% accuracy	These findings demonstrate DL's practicality for predictive neuroimaging biomarkers. Further, it may entail independent large-cohort clinical trial validation.	[145]
	Two-level LSTM and a CNN	To classify recordings and distinguish healthy and dementia patients accurately and cost-effectively	CNN: mean AUC of 0.805 ± 0.027 LSTM: mean AUC of 0.740 ± 0.017	Although robust cross-validation highlighted consistent performance, external validation across diverse cohorts remains essential to confirm their applicability across broader contexts.	[146]
	GRU	To differentiate between healthy and MCI patients efficiently.	A peak accuracy of 96.91%	It can serve as a reliable biomarker for developing an automated, real-time MCI detection approach.	[147]
	3D-CNN and FSBi-LSTM	Designing a framework for AD that addresses the challenges of traditional ML, such as time constraints and manual feature extraction.	94.82%, 86.36%, and 65.35% for distinguishing AD, pMCI, and sMCI from NC respectively	Longitudinal MRI data and overcoming the cascade of CNN and LSTM for lesion structure identification could be incorporated to offer supplementary insights into disease progression.	[148]
Emotion Recognition	NN	Comparing DL and conventional ML techniques for SER using available datasets, providing practical insights.	Recent databases: average sample duration of 2.8 seconds; TESS: average sample duration of 2.1 seconds (outlier)	Due to the challenging nature of shorter emotional speech utterances, this area is earmarked for future research, with subsequent investigations focusing on robust, dataset-agnostic solutions.	[149]
	RNN	To leverage current advances in DL for audio-visual emotional recognition	Exhibits superior performance compared to existing methods, with visual feature extraction network surpassing state-of-the-art results on the Google FEC and AffectNet datasets.	Despite their large dataset, further exploration is required to determine how well the benefits of ImageNet's unlabeled data transfer to facial expression analysis.	[150]
	DNN, VMD	To recognize the shared EEG patterns corresponding to emotions across subjects	DNN outperforms SVM classifiers in subject-independent emotion recognition.	Key strength of this approach lies in utilizing separate EEG data for model training and testing, enabling accurate emotion recognition for individuals who were not part of the original training dataset.	[151]
	LSTM	Developing a DL technique to categorize emotional states from EEG signals	82.01% average accuracy	The algorithm's assessment of ToC across a large dataset, with deep algorithm parameter constraints, had a minor impact on processing speed.	[152]
Sleep Analysis	1D-CNN	To classify sleep stages analyzing EEG and EOG data	Achieved the highest accuracies across 2-6 sleep classes in the respective dataset.	The model's clinical potential is evident, yet its evaluation focuses on signal-level criteria. Enhancing its application could involve utilizing extensive PSG datasets and patient-level analysis.	[153]
	CNN	To devise automatic sleep stage annotation to monitor sleep disorders	84.26% overall accuracy	Like other DL approaches, abundant sleep stage samples are necessary for discriminative feature learning in training. The sequence-to-sequence model requires sufficient 30-second EEG epochs per time step for accurate input scoring.	[154]
	MRCNN, AFR	To fabricate a novel attention-based architecture for sleep stage classification from single-channel EEG	Performance evaluation on three public datasets confirmed its stability across varying numbers of heads.	Exploring domain adaptation techniques for classifying unlabeled sleep data from diverse datasets could enhance generalizability.	[155]
	CNN	Developing a system that takes single-lead ECG signals and detects the OSA condition	An accuracy boost of over 9% compared to prior research	The complexity doesn't hinder deploying the algorithm on a microcontroller, as ARM-based microcontrollers have demonstrated the implementation of such systems.	[156]
Stress Monitoring	CNN and wireless network sensor	To employ DL to gauge variations in stress intensity for detecting mental stress	Neural signals greatly improved the efficacy of the classification model for evaluating psychological stress.	It should encompass more individuals and incorporate real-life stress scenarios alongside laboratory experiments.	[159]
	Feedforward ANN	To develop DL models for stress recognition using multimodal dataset recorded from wearable sensors.	84.32% and 95.21% accuracy rates for three-class and binary classification, respectively	The study could integrate self-reported data from participants using structured surveys and combine diverse sources.	[160]
	BiLSTM and CNN	Detecting psychological stress in real-time using DL from ECG signals	0.865 accuracy across 3 stress levels using a ten-second ECG signal	The development process overlooked personality variations, which could significantly influence performance enhancement.	[161]
	DNN	To accurately detect work-related stress using multimodal signals	73.3% accuracy (AUC: 0.822, F1 score: 0.700) and 54.4% accuracy (AUC: 0.727, F1 score: 0.508) for two-level and three-level stress classification, repectively	The analysis revealed that overlapping samples contributed to performance degradation, and the importance of signals varied based on the stress classification task.	[162]

Table 5 (*continued*)

Applications	Model/ network	Objective	Outcome/accuracy	Remarks	Ref.
Neurofeedback	ResNet50, and SVM	To evaluate the outcomes of neurofeedback training for addressing CNP in paraplegic patients using a BCI that leverages DL features.	99.94 ± 0.05% accuracy	The findings of this study not only offer important implications for increasing the efficiency of MI-EEG-based BCIs, but also open avenues for future research in this domain.	[163]
	DBS electrodes	Investigating the potential of neurofeedback as an intrinsic modulation approach	Patients expeditiously acquired real-time volitional regulation over ongoing deep-brain oscillatory activity.	There is a need to fully explore the extent of voluntary self-regulation of deep brain oscillatory activity and its impact on motor outcomes, considering the study's limited intervention period.	[164]
	CNN	To analyze the influence of hyperparameter optimization on classifier performance through statistical analysis	Notably, CNN exhibited superior performance compared to the standard methods.	The variations in performance among the three CNNs were negligible. Like, the effects of intra-subject and inter-subject optimization methods were insignificant.	[165]
	CNN	Creating a calibration-free and continuously decodable MI-BCI using a novel CNN-based learning approach	71.49% and 70.84% average decoding accuracies using Adam and SGDM training techniques	Minimizing calibration demands and offering continuous feedback play a crucial role in enhancing the user experience, thereby increasing the potential for successful neurorehabilitation results.	[166]

for early detection and improved accuracy [167]. It has become possible to develop advanced screening tools that can accurately identify individuals with cognitive impairment, including MCI and dementia due to AD and other disorders, through the utilization of DL-driven techniques. Targeting a wide range of populations with different conditions and stages of cognitive disorders, DL models can determine the importance of different features from patient data, eliminate irrelevant ones, and reduce the intricacy of the screening process, leading to improved diagnostic accuracy [168]. Therefore, the advanced diagnostic capabilities of DL enable more precise and personalized assistance in managing AD and other cognitive-related conditions [169].

DL can benefit cognitive healthcare by enhancing the diagnosis of dehydration through the analysis of body signals, such as electrodermal activity and heart rate variability. By analyzing multimodal data from different sensors, DL models can provide personalized detection of dehydration, as well as better understand and manage cognitive and emotional states [170]. DL has also shown impressive performance in stroke research through its image processing capabilities, including the analysis of CT and MRI scans [171]. Integrating DL with IoT frameworks can enable patient-centric healthcare solutions and real-time intelligent decision-making, leading to improved remote healthcare services like remote surgery, better evaluation of emotional states in patients with conditions, such as insomnia, depression, and autism and optimized utilization of medical resources [172]. Lastly, DL can offer healthcare practitioners more precise insights in brain imaging and neurocognitive assessments, leading to improved medical practices and better patient care in cognitive healthcare.

6.1.2. *Personalized treatments*

DL has the possibilities to revolutionize cognitive healthcare through its contribution to precision medicine and personalized treatment strategies. By leveraging patient data, including behavioral determinants, medical history and environmental knowledge, DL algorithms can precisely characterize health states and cognitive disease conditions for individuals. In addition, DL can address challenges, such as incorporating genetic data into Electronic Medical Records (EMRs), handling unstructured data in radiology and pathology reports, and standardizing medical nomenclature [173]. With a deeper understanding of these diverse patient data, DL models can analyze complex information and identify personalized therapies for cognitive-related conditions [174]. This empowers healthcare professionals to practice personalized treatment strategies, leading to improved patient outcomes, optimized drug combinations, early disease detection, and the delivery of individualized care that may have been previously unrealized [175].

DL presents personalized treatment approaches by continuously monitoring and analyzing stress levels, sleep states, and physiological signals during cognitive training sessions. Utilizing wearable physiological sensors and mobile applications equipped with DL algorithms, medical specialists can create tailored therapy plans for older adults with MCI and frailty conditions [176]. The use of DL enables early detection of migraine attacks and sleep apnea, facilitating timely interventions and preventive measures to address potential health issues [170]. DL models can also predict treatment outcomes for medications, psychotherapies, digital interventions, and neurobiological therapies [177]. By accurately estimating inpatient costs and lengths of stay following surgeries, DL contributes to better patient management and more equitable payment models [178]. Embracing DL thus offers promising benefits for personalized treatment strategies, ultimately enhancing patient care and well-being.

6.1.3. *Early intervention*

DL can significantly benefit cognitive healthcare by predicting treatment responses and identifying risk factors for the development of psychiatric disorders. Analyzing multi-source data, such as clinical questionnaire items, EEG signals, brain structural and functional MRI data, and gene expression patterns, DL models can help identify patients at risk of developing mental health conditions, such as depression, anxiety, or schizophrenia, at an early stage [179]. DL and AI-driven interventions can create personalized mental healthcare solutions accessible through smartphones and wearables. Processing data from online platforms, DL can contribute to anti-stigma initiatives for young people, especially in low-resource settings, encouraging open conversations about mental health and reducing barriers to early intervention. Thus, the capabilities of DL hold immense promise for early intervention, enabling targeted and personalized support, reducing stigma, and fostering overall mental well-being [180].

By leveraging sophisticated technology, DL models can analyze diverse data sources, such as MRI scans and biomarkers (i.e., chemicals and blood flow), to detect AD at its early stages. They enable researchers to predict AD conversion in individuals with MCI within a 3-year period. This ability to identify AD at an early stage allows timely clinical management, personalized treatment planning, and participation in clinical drug trials, potentially slowing down the disease progression, minimizing brain damage, and reducing healthcare costs [181]. Moreover, the use of non-invasive and cost-effective predictors in DL models makes early detection more accessible and scalable, paving the way for personalized and effective interventions at the earliest disease stages [182]. Likewise, early intervention through DL can effectively help to monitor and regulate mental health and stress-related factors, such as anxiety, hypertension, and cognitive decline, leading to the prevention of long-term health issues and improved patient outcomes [183].

6.1.4. Remote monitoring

In cognitive healthcare, DL accelerates remote and continuous monitoring of patients, allowing timely interventions and personalized treatment plans. The capabilities of DL techniques extend BCI systems, facilitating better interpretation of brain patterns and providing smart cognitive healthcare, such as converting thought processes to speech and recognizing human emotions. In Ambient Assisted Living (AAL) scenarios, DL can be applied to EEG, ECG and EOG signals to monitor and analyze the sleep patterns of patients [184]. Leveraging DL models on EEG data, remote monitoring also enables enhanced diagnosis and risk assessment of epilepsy, overcoming visual inspection limitations, while IoT-based continuous tracking of vital signs and movement patterns aids in the early detection of cognitive disorders like Parkinson's disease [172]. Remote monitoring using DL also empowers healthcare professionals with valuable insights and decision-making by providing early detection of brain-related disorders, such as stroke, dementia and depression [185].

Integrating IoT with DL techniques can assist remote monitoring of patients' health conditions through wearable and implanted devices. Such systems are capable of real-time monitoring of patients' physiological parameters and daily activities in AAL scenarios, which allow healthcare experts like caregivers, doctors, and physiotherapists to track patients' health conditions, vital signs, and activities from a distance [186]. Different mental health conditions, particularly depression, stress, and anxiety, can be detected at an early stage using digital biomarkers and bio-signals collected from individuals in their daily activities [187]. Remote monitoring supports telehealth services, enabling patients to receive cognitive assessments and interventions from the comfort of their homes, thereby increasing accessibility and reducing healthcare costs. Finally, remote monitoring ensures that healthcare providers are promptly notified in case of any emergency or critical change, facilitating immediate support and care for patients' cognitive well-being [188].

6.1.5. Assistive technologies

DL algorithms can enhance the effectiveness of assistive technologies by customizing cognitive training based on individual needs and progress. These technologies mainly aim to decrease cognitive impairment and improve cognitive skills like memory, attention, and planning through visual memory training and various cognitive games [189]. Assistive technologies, employing DL can also be beneficial to older adults experiencing cognitive impairment or cognitive decline [190]. In particular, mobile health (mHealth) applications offer simple and effective solutions for individual patients with dementia, including AD, and their caregivers. Integrating the capabilities of DL into mHealth apps can facilitate personalized cognitive training based on the activities of daily living, continuous and remote monitoring of cognitive health, early detection through dementia screening tools, promotion of reminiscence and socialization, and valuable support for caregivers, ultimately enhancing the overall quality of life for patients with cognitive disorders and empowering the dementia community [191].

6.1.6. Reduced healthcare costs

DL algorithms can automate various processes, analyze a high volume of data, and provide personalized insights, which can lead to increased efficiency in cognitive healthcare delivery and management. Early detection of stress, anxiety, and hypertension using DL and wearable devices can enable timely interventions, potentially preventing the progression of long-term mental disorders and resulting in reduced resource utilization, shorter hospital stays, and optimized treatment plans [183]. Furthermore, AI-driven interventions, such as telehealth and chatbots for psychotherapy support and symptom monitoring, can offer cost-effective alternatives to traditional in-person therapies, making healthcare more accessible and affordable for individuals, particularly those in remote areas [192]. Unlike traditional approaches, DL can also automate tasks like sleep scoring in sleep medicine, resulting in time and resource savings for healthcare professionals while reducing overall costs [193]. A summary of recent studies conducted on the benefits of DL is given in Table 6.

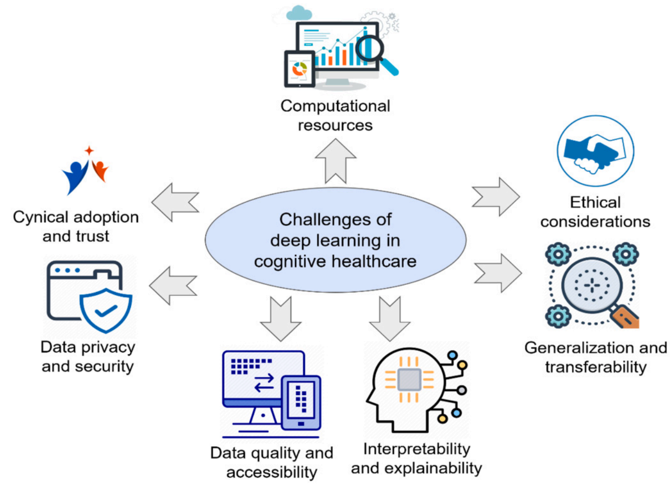

Fig. 3. Challenges of DL in cognitive healthcare.

6.2. Challenges

Although integrating DL into cognitive healthcare offers numerous advantages, there exist key obstacles that must be addressed. Concerns related to data privacy and security, data quality and accessibility, interpretability and explainability, generalization and transferability, computation resources, clinical adoption, trust and ethical considerations collectively hinder the effective implementation of DL-based solutions in cognitive healthcare. Table 7 presents various challenges associated with DL and the potential solutions deliberated in recent research. Fig. 3 illustrates a visual representation of the challenges that DL faces in the field of cognitive healthcare.

6.2.1. Data privacy and security

The advancement of DL in cognitive healthcare raises significant concerns regarding the privacy and security of health data, which is inherently sensitive and susceptible to data breaches. Patient consent emerges as a pivotal aspect in addressing these concerns since healthcare organizations might employ patient data for training DL models without obtaining adequate individual consent [29]. Deepfakes, AI-synthesized media including images, audio, and video, pose a growing concern in cognitive healthcare as they can be used to impersonate individuals convincingly, raising the alarm about potential privacy breaches and fraudulent activities. Current privacy measures fail to adequately address the potential risks, which can lead to exploiting sensitive patient health information, manipulating medical images, and triggering false insurance claims [194]. With the development of telemedicine and remote health monitoring, it has become very crucial to safeguard the privacy and security of patient data.

When DL techniques are integrated into edge intelligence for real-time patient monitoring, remote interaction, and healthcare support, the sensitive medical data being processed and transmitted becomes vulnerable to breaches and unauthorized access. The collaborative nature of cloud, fog, and edge computing in implementing these techniques can potentially expose patient information to privacy risks [184]. Resource-limited body sensors and unsecured IoT devices are vulnerable to security flaws and cyber-attacks, allowing attackers to compromise sensors, misuse sensitive patient data, and disable critical services [172]. Additionally, the exploitation of sensitive patient data, particularly emotions and medical information, poses significant privacy risks since malicious actors could expose private medical details, demand ransom, or sell the data for fraudulent purposes, potentially compromising patient confidentiality and trust in cognitive healthcare systems [195]. Data privacy

Table 6
Benefits/advantages of using DL in cognitive healthcare.

Benefits	Description	Remarks	Ref
Improved diagnosis	DL has the potential to significantly impact the field of cognitive healthcare, especially in clinical neurosciences, where it can aid in diagnosing neurologic diseases and analyzing medical images.	The advanced diagnostic capability provided by DL paves the way for improved accuracy, early detection, and more precise and personalized assistance.	[167]
	By utilizing DL models, it has become possible to develop advanced screening tools that can accurately identify individuals with cognitive impairment, including MCI and dementia due to AD and other disorders.	These models can determine the significance of various features, discard irrelevant ones, and reduce the complexity of the screening process, leading to improved diagnostic accuracy and the ability to target appropriate populations with different conditions and stages of cognitive disorders.	[168]
	DL can benefit cognitive healthcare by enhancing dehydration diagnosis through analyzing body signals, such as heart rate variability and electrodermal activity.	By analyzing multimodal data, DL models can provide personalized detection of dehydration, as well as better understand and manage cognitive and emotional states.	[170]
	Integrating DL with IoT frameworks can enable patient-centric healthcare solutions and real-time intelligent decision-making.	These frameworks lead to improved remote healthcare services like remote surgery, better evaluation of emotional states in patients with conditions such as insomnia, depression, and autism and optimized utilization of medical resources.	[172]
Personalized treatments	Certain challenges, such as incorporating genetic data into EMRs, can be addressed by DL-driven solutions.	DL is capable of handling unstructured data in radiology and pathology reports and standardizing medical nomenclature.	[173]
	With a deeper understanding of diverse patient data, DL models can analyze complex information and identify personalized therapies for cognitive-related conditions.	This empowers healthcare professionals to practice personalized treatment strategies, leading to improved patient outcomes, optimized drug combinations, early disease detection, and the delivery of individualized care that may have been previously unrealized.	[174,175]
	DL enables early detection of migraine attacks and sleep apnea.	This facilitates timely interventions and preventive measures to address potential health issues.	[170]
	DL can accurately estimate inpatient costs and lengths of stay following surgeries.	Thus, embracing DL contributes to better patient management and more equitable payment models.	[178]
Early intervention	DL can be used to analyze data from different sources, such as clinical questionnaire items, EEG signals, brain structural and functional MRI data, and gene expression patterns.	Accordingly, DL can help identify individuals at risk of developing mental health conditions, such as depression, anxiety, or schizophrenia, at an early stage.	[179]
	Processing data from online platforms, DL can contribute to anti-stigma initiatives for young people, especially in low-resource settings, encouraging open conversations about mental health and reducing barriers to early intervention.	The capabilities of DL hold immense promise for early intervention, enabling targeted and personalized support, reducing stigma, and fostering overall mental well-being.	[180]
	By leveraging sophisticated technology, DL models can analyze diverse data sources, such as MRI scans and biomarkers (i.e., chemicals and blood flow), to detect AD at its early stages, and predict the conversion to AD in individuals with MCI within a 3-year period.	This ability to identify AD at an early stage allows timely clinical management, personalized treatment planning, and participation in clinical drug trials, potentially slowing down the disease progression, minimizing brain damage, and reducing healthcare costs.	[181]
	Early intervention through DL can effectively help to monitor and regulate mental health and stress-related factors, such as anxiety, hypertension, and cognitive decline.	It leads to the prevention of long-term health issues and improved patient outcomes.	[183]
Remote monitoring	DL extends BCI systems, while optimizing cognitive healthcare and sleep pattern analysis in AAL scenarios using EEG, ECG, and EOG signals.	Providing better interpretation of brain patterns, such as converting thought processes to speech and recognizing human emotions, monitoring and analyzing sleep patterns of the patients are the potential benefits.	[184]
	Leveraging DL models on EEG data, remote monitoring also enables enhanced diagnosis and risk assessment of epilepsy, overcoming visual inspection limitations, while IoT-based continuous tracking of vital signs and movement patterns aids in the early detection of cognitive disorders like Parkinson's disease.	Remote monitoring using DL empowers healthcare professionals with valuable insights and decision-making by providing early detection of these disorders.	[172,185]
	Integrating IoT with DL techniques is capable of real-time monitoring of physiological parameters and daily activities of patients in AAL scenarios.	This allows healthcare experts like caregivers, doctors, and physiotherapists to track patients' health conditions, vital signs, and activities from a distance.	[186]
	Remote monitoring facilitates telehealth services, enabling patients to receive cognitive assessments and interventions from the comfort of their homes.	It ensures that healthcare providers are promptly notified in case of any emergency or critical change, facilitating immediate support and care for patients' cognitive well-being.	[188]
Assistive technologies	DL algorithms can enhance the effectiveness of assistive technologies by customizing cognitive training based on individual needs and progress.	Assistive technologies, employing DL can be beneficial to older adults experiencing cognitive impairment or cognitive decline.	[190]
	Integrating the capabilities of DL into mHealth applications offers simple and effective solutions for individuals living with dementia, including AD, and their caregivers.	This facilitates personalized cognitive training based on the activities of daily living, continuous and remote monitoring of cognitive health, and early detection through dementia screening tools, ultimately enhancing the overall quality of life for individuals with cognitive disorders and empowering the dementia community.	[191]
Reduced healthcare costs	Early detection of stress, anxiety, and hypertension using DL and wearable devices can lead to increased efficiency in cognitive healthcare delivery and management.	The potentiality of DL prevents the progression of long-term mental disorders, resulting in reduced resource utilization, shorter hospital stays, and optimized treatment plans.	[183]
	AI-driven interventions, such as telehealth and chatbots for psychotherapy support and symptom monitoring, can offer cost-effective alternatives to traditional in-person therapies.	Thus, the cognitive healthcare sector can be more accessible and affordable for patients, particularly those in remote areas.	[192]

must be ensured to maintain integrity and trust in cognitive healthcare services [175].

6.2.2. Data quality and accessibility

Ensuring data quality in DL techniques involves acquiring and utilizing high-quality data that is representative, reliable, and relevant for training DL models in this domain. Data quality is a critical factor in the success and reliability of DL algorithms, and it becomes even more crucial in cognitive healthcare due to several reasons, such as limited data resources, data collection and annotation strategies, data variability, noise and artifacts, and standardization [193,196]. The presence of outliers within training datasets can also result in non-convergence or biases in parameter estimations. Simultaneously, limited datasets might substantially deteriorate the predictive capabilities of DL models. Maintaining data quality becomes more challenging, where integrating diverse data sources, harmonizing data for analysis, and addressing inconsistencies across varied protocols can negatively impact prediction accuracy and outcomes in cognitive healthcare [197].

Moreover, cognitive healthcare data obtained from different modalities require specialized expertise for accurate interpretation, which makes annotating patient data a complex and resource-intensive task. The scarcity of extensive and well-annotated medical datasets also poses a significant challenge for training large DL models from scratch. The sensitivity concerns related to patient information in clinical data further limit the applicability of publicly available models, such as GPT-4, in this domain [198]. Existing patient data mainly come from standardized tests, focusing on only symptom-related evidence for a particular disease, overlooking other related issues, such as cellular, endophenotype, epigenetics, and neurophysiological factors. This lack of comprehensive data impedes the understanding of mental illnesses [199]. Thus, the effectiveness of DL techniques can be hindered by data quality and accessibility issues, ultimately affecting the robustness and reliability of these learned models [200].

6.2.3. Interpretability and explainability

DL models are generally considered “black boxes” because they learn complex, non-linear relationships from data, making it challenging for humans to understand their decision-making process. Therefore, the interpretability and explainability of DL models have become crucial for gaining trust from medical professionals, ensuring patient safety, facilitating research insights, and addressing ethical concerns related to biases and fairness in cognitive healthcare. The lack of consensus on the definition of interpretability and explainability is a major challenge, leading to difficulties in assessing the quality of existing techniques and comparing different frameworks [201]. However, limited understanding and confidence in the decision-making process necessitate the development of transparent algorithms and interpretable models in order to build trust and foster the acceptance of AI applications in cognitive healthcare [202].

Since interpretability and explainability require a proper interface between DL algorithms and human cognitive abilities to understand the patterns of the extracted data, they pose significant difficulties in this domain [203]. There is a growing focus on developing interpretable models to extract relevant features that can explain disease severity and track disease progression. DL models are being explored and explained to recognize human activities, and different approaches, such as computing the importance of input parts and making sequential selections for model training, are being investigated to enhance interpretability and extract meaningful insights [204]. In addition, explainable techniques can be used to develop fully transparent models, resulting in improved model performance and consistent representations aligned with human reasoning and understanding [205]. These efforts aim to interpret human behavior and cognitive processes, which are important for diagnosing cognitive disorders and improving patient outcomes in clinical settings.

6.2.4. Generalization and transferability

Generalization and transferability in DL enable a model to perform well on new, unseen data beyond the training phase. Despite the success of existing DL applications, their widespread adoption in real-world healthcare settings is limited due to concerns about their efficacy across different scenarios. DL algorithms often overfit training data, becoming hyper-specialized for certain hospitals or patient demographics and less effective for broader populations. The siloed nature of healthcare data and heterogeneity across systems further complicate the development of generalizable models [167]. The application of DL in automated sleep scoring is a promising area for cognitive healthcare. Although DL algorithms have demonstrated superior performance in young and healthy individuals, they encounter difficulties in accurately identifying sleep disorders in older patients. However, the availability of larger and diverse datasets has the potential to address cognitive biases and human variations, leading to standardized and interpretable solutions for sleep disorder diagnosis and assessment, ultimately improving healthcare outcomes [193].

The generalizability and transferability of DL models rely on having representative training datasets, with a diverse feature set reflective of the broader population. However, patient data often lack diverse subgroups, leading to sampling bias. Moreover, the incorporation of heterogeneity in the data depends on how researchers conceptualize and appreciate cognitive features, potentially impacting the performance and generalizability of the algorithms [206,207]. Even within the same hospital, models trained on one electronic health record (EHR) system can deteriorate when tested on data from a new EHR system. While algorithms have been proposed to address distribution shifts, they often require assumptions and have limitations, emphasizing the importance of regularly monitoring data shifts and considering potential model retraining [208]. Complying with regulations and protecting patient data remain challenges in cognitive healthcare, even though using data from multiple institutions can boost model performance [194].

6.2.5. Ethical considerations

AI, especially DL has the immense potential to revolutionize cognitive healthcare delivery, offering new ways for diagnosis, treatment, and medical condition management. While DL-enabled technologies can offer promising advancements in cognitive healthcare, they also introduce ethical dilemmas related to patient privacy, data security, bias in algorithms, and the appropriate use of AI in decision-making [209,210]. Besides, it is also important to assess how these applications will impact the well-being and future of society [211]. Balancing technological advancements with ethical considerations is crucial to ensuring that DL-driven cognitive healthcare solutions are beneficial and trustworthy for patients, healthcare providers and society. By addressing ethical concerns and promoting responsible utilization of DL, the positive impacts on cognitive healthcare can be maximized while safeguarding the welfare and interests of all stakeholders involved.

By leveraging computing capabilities, machine intelligence, robotics, and Intelligent Assistive Technologies (IATs) are designed to provide assistance for individual patients with dementia and their caregivers. However, the use of IATs in dementia care also raises significant ethical challenges related to the vulnerability of older individuals, data privacy, algorithmic transparency, and the necessity for user-centered design [212]. Moreover, applying conventional moral frameworks to non-organic intelligence, like DL or the transformation of a human brain into an inorganic computer, can lead to ethical issues due to the unique nature and characteristics of these entities [213]. Since there is an increasing demand for DL-enabled technologies in cognitive healthcare, healthcare providers should proactively seek opportunities for professional growth and education before incorporating these technologies. They must consider the potential impacts on their patients’ privacy to ensure ethical practices in the future of cognitive healthcare [214].

6.2.6. Computational resources

Although DL has emerged as a cutting-edge technique for various tasks in cognitive healthcare, the algorithms require high computational resources during training. Difficulties arise when substantial volumes of big data have to be processed through wireless communication, including transmission delays, frequent packet drops, and limited availability of transmission channels [215]. Edge intelligence and IoT-enabled devices also possess limited computational capacity and battery life, necessitating a balanced allocation scheme between the main server and other computing devices. However, the need for frequent retraining and updates of DL-based models can further result in substantial computational demands, even with lightweight models [184]. In particular, DL models can facilitate early identification and diagnosis of AD, yet the training and utilization of these models require considerable processing power and memory [216].

6.2.7. Clinical adoption and trust

The rapid advancements in DL hold the potential to revolutionize cognitive healthcare through personalized, predictive and precise healthcare solutions [217]. But the absence of intuitiveness and the difficulty in providing explanations make predictive modeling in healthcare a challenging endeavor. Due to the lack of transparency, these attributes contribute to the constrained acceptance and practicality of predictive solutions within cognitive healthcare contexts. Therefore, the healthcare sector requires an efficient strategy to improve the comprehensibility of predictive solutions [203,218]. It has been suggested that simplifying DL models could increase the potential for their adoption and trust in clinical settings by improving the understanding of their techniques.

These challenges are applicable to the majority of DL applications in cognitive healthcare. Beyond these, there are additional challenges, such as handling disease progression and heterogeneity, and implementing multi-view learning in neuroimaging. Validating models with additional imaging planes is particularly challenging due to the lack of comprehensive datasets for detecting neurological conditions like AD and MCI. The absence of critical biomarkers, genetic information, lifestyle factors, and other diverse influences can limit the insights drawn from these datasets. Small sample size in these datasets poses further challenges, potentially affecting the generalizability of the findings. This issue is also evident in depression monitoring applications, where experiments often involve a limited number of participants and an unequal distribution of depression cases. Moreover, compatibility issues arise when fine-tuning trained models on other small or limited datasets. Physical data from wearable signals often fails to accurately capture the key biological characteristics of neurons, with abrupt oscillations causing inconsistent performance across different stages of analysis. Including multimodal data, while potentially beneficial, increases model complexity due to a higher number of parameters, leading to longer execution times and greater resource demands. To enhance interoperability and standardization in cognitive healthcare, it is essential to develop long-term monitoring solutions and more accessible clinical models in the future.

7. Future directions in advancing cognitive healthcare through DL

As the integration of DL continues to evolve, exploring its potential in cognitive healthcare applications holds the key to a number of possibilities in the upcoming years. Further research should concentrate on multimodal signal analysis, transfer learning, explainable AI, personalized cognitive healthcare, longitudinal monitoring, data security and privacy preservation measures and real-world clinical validation and adoption. These areas will contribute to shaping the future landscape of cognitive healthcare as shown in Fig. 4.

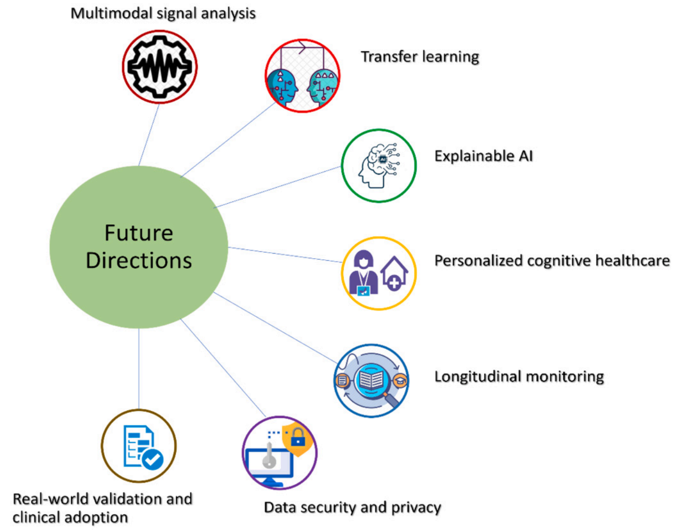

Fig. 4. Future directions of cognitive healthcare through DL.

7.1. Multimodal signal analysis

Multimodal signal analysis in DL refers to the process of analyzing and integrating data from multiple sources or modalities, such as medical imaging, EEG, genetic information, and behavioral data, to gain a comprehensive understanding of a patient's cognitive health. By combining information from multiple sources, multimodal signal analysis can provide deeper insights into the underlying mechanisms of cognitive diseases and mental health conditions [219]. For instance, the potential of DL techniques and multimodal processing techniques on a larger number of samples should be explored in order to develop more reliable and efficient automated dementia diagnosis tools [220]. However, the complexity of multimodal signal fusion increases with the quantity of connected sensors and the number of users or patients using the system. Different factors, such as hardware failures, communication issues, and uncertainties related to data from heterogeneous sensors, can influence the system's performance. Therefore, developing standardized and simpler fusion approaches in cognitive healthcare should be focused in future research [221].

Cognitive healthcare, enabled by IoT, smart sensors, cloud technology, and AI, has transformed healthcare services in smart city applications. The interconnected devices and sensors in the healthcare systems learn from the environment, process real-time multimodal data, and make intelligent decisions with minimal human intervention [222]. Integrating advanced DL techniques, with state-of-the-art methods like ANNs, CNNs, RNNs, and fuzzy logic should be focused on in the future. Moreover, different advanced fusion techniques, such as multi-sensor data fusion, multi-feature fusion, multi-atlas label fusion, multi-view fusion, and multi-modality data fusion, should be prioritized in smart cognitive healthcare [223]. Researchers should also address various influencing factors, estimate additional vital signs for real-world applications, utilize diverse and high-quality datasets to analyze different methods, and develop more sophisticated DL models and architectures [224]. A deeper understanding of various DL approaches is crucial in integrating these networks into cognitive healthcare applications.

7.2. Transfer learning

Transfer learning refers to the practice of using pre-trained DL architectures on related medical tasks to adapt and improve the performance of models in diagnosing and predicting cognitive health conditions, even with limited data in this domain. Although DL methods, such as CNNs and sparse autoencoder have shown to be effective in healthcare, they require a large volume of labeled medical images for training. In such cases, transfer learning methods present a solution by leveraging pre-trained models and adapting them with smaller datasets [225]. For example, transfer learning in ensemble-based models can predict the risk of AD dementia onset in a relatively younger population, potentially up

Table 7
Challenges of DL and the possible solutions in cognitive healthcare.

Challenges	Description	Possible Solutions	Ref
Data privacy and security	Healthcare organizations employing patient data for training DL models without obtaining adequate patient consent raise privacy and security concerns.	Healthcare organizations must obtain explicit and informed consent from patients before utilizing their data for training DL models.	[29]
	Deepfakes, AI-synthesized contents raise concerns due to their potential for convincing impersonation, leading to privacy breaches, fraudulent activities and manipulation of patient health information.	Developing advanced detection tools to identify deepfakes, implementing stricter data-sharing protocols with encryption, and raising awareness can address this issue.	[194]
	Integrated DL in edge intelligence can make sensitive patient data vulnerable to breaches and unauthorized access during processing and transmission.	Implementing robust encryption methods for data transmission and utilizing secure authentication protocols, and access controls should be emphasized while leveraging edge computing approaches.	[184]
	The vulnerability of resource-limited body sensors and unsecured IoT devices enables attackers to compromise sensors, misuse patient data, and disable critical services.	Considering robust security measures such as encryption, regular software updates, and network segmentation to isolate critical services from potential threats can mitigate this challenge.	[172]
	Exploiting sensitive patient data, including emotions and medical information poses significant privacy risks, since malicious actors could expose medical details, demand ransom, or sell the data fraudulently.	Possible solutions include implementing robust encryption and access controls for patient data, and continuous monitoring to prevent unauthorized access, data breaches, and malicious activities.	[195]
Data quality and accessibility	Limited data resources, data collection and annotation strategies, data variability, noise and artifacts, and standardization pose challenges while ensuring high-quality data for DL algorithms.	Applying data augmentation techniques, enhancing data annotation methods, and implementing preprocessing steps can contribute to maintaining the data quality for DL algorithms.	[193,196]
	Integrating diverse data sources, harmonizing data for analysis, dealing with outliers and addressing protocol inconsistencies can negatively impact the prediction accuracy and outcomes of DL models.	Developing robust data integration and preprocessing pipelines, using standardized data formats, and detecting outliers can minimize this problem.	[197]
	Lack of comprehensive, well-annotated medical data across modalities is a significant challenge for training large DL models from scratch, while the sensitivity concerns related to patient information further limit the applicability of publicly available models.	Developing collaborative data annotation, adapting pre-trained models to specific tasks, and implementing privacy-preserving techniques should be emphasized to address this issue.	[198]
	Existing patient data primarily come from standardized psychology tests, mainly focusing on disease-specific symptoms and overlooking related issues, such as neurophysiological factors, which hinder a comprehensive understanding of mental illnesses.	Possible solution include integrating multi-modal data collection techniques that encompass diverse biological and neurophysiological markers, and utilizing advanced technologies like neuroimaging to facilitate a more comprehensive understanding of mental health conditions and their underlying mechanisms.	[199]
Interpretability and explainability	The lack of consensus on the definition of interpretability and explainability leads to difficulties in assessing the quality of existing techniques and comparing different frameworks.	Standardizing definitions, developing benchmarking protocols, facilitating community discussions, and emphasizing transparency in documentation can mitigate the challenge.	[201]
	Limited understanding and confidence in the decision-making process necessitate interpretable models and transparent algorithm development.	The possible solutions are developing explainable techniques, creating model visualizations, and offering insights into the decision-making process of DL algorithms.	[202]
	A rising demand exists for interpretable models to extract relevant features that explain disease severity and track disease progression.	Exploring DL models and different approaches, such as assessing input importance or sequential feature selection during training, can enhance interpretability and extract meaningful insights.	[204]
Generalization and transferability	DL algorithms tend to overfit training data, becoming hyper-specialized for certain hospitals or patient demographics and thus limiting their generalizability and transferability across broader populations.	To address this challenge, it is important to consider data augmentation techniques, transfer learning, and FL approaches, which can effectively generalize across diverse healthcare settings and patient demographics.	[167]
	Although DL algorithms have demonstrated superior performance in young and healthy individuals, they encounter difficulties in accurately detecting sleep disorders in older patients.	Larger and diverse datasets have the potential to mitigate cognitive biases and human variations, resulting in standardized and interpretable solutions for sleep disorder diagnosis and assessment.	[193]
	The incorporation of data heterogeneity depends on how researchers conceptualize and appreciate cognitive features, potentially impacting the performance and generalizability of the algorithms.	Interdisciplinary collaboration between researchers and domain experts, standardization of guidelines for feature selection, and utilization of transfer learning techniques can address this issue.	[206,207]
	To address distribution shifts in patient data, DL algorithms often require assumptions and have limitations.	It is important to monitor data shifts and consider potential model retraining regularly.	[208]
Ethical concerns	DL-enabled technologies raise ethical issues regarding patient privacy, data security, algorithmic bias, and the responsible use of AI in decision-making.	Balancing technological advancements with ethical considerations is crucial to ensure that DL-driven solutions are beneficial and trustworthy for all stakeholders.	[209,210]
	Utilizing IATs in dementia care also raises ethical challenges related to the vulnerability of older individuals, data privacy, algorithmic transparency, and the need for user-centered design.	Implementing robust data privacy measures, ensuring algorithmic transparency and prioritizing user-centered design are the possible solutions to address this challenge.	[212]
	Applying conventional moral frameworks to non-organic intelligence, like DL or the transformation of a human brain into an inorganic computer, can lead to ethical issues due to these entities' unique nature and characteristics.	Developing new ethical paradigms that consider these entities' distinct nature and characteristics and fostering interdisciplinary collaborations to establish comprehensive guidelines can facilitate cognitive healthcare.	[213]
Computational resources	Difficulties arise while processing substantial volumes of big data via wireless communication, encompassing transmission delays, frequent packet drops, and limited availability of transmission channels.	Implementing data compression, optimizing network resources, integrating predictive analytics, and leveraging hybrid communication technologies can address this challenge.	[215]
	The need for frequent retraining and updates of DL-based models can further result in substantial computational demands, even with lightweight models.	Adopting efficient incremental learning strategies, utilizing transfer learning techniques, and leveraging model compression methods are the potential solutions to mitigate this problem.	[184]
	DL models can facilitate early detection and diagnosis of AD, yet the training and utilization of these models require considerable processing power and memory.	This problem can be resolved by utilizing distributed computing frameworks, optimizing model architectures, and employing hardware accelerators.	[216]
Clinical adoption and trust	Lack of intuitiveness and difficulty in providing explanations for predictive modeling hinder the acceptance and practicality of predictive solutions.	Improving model comprehensibility can boost understanding, adoption, and trust in predictive modeling in clinical settings.	[218]

to 14 years in advance [226]. Moreover, researchers can improve prediction accuracy and facilitate early detection of dementia for effective preventive interventions through the integration of all subcortical brain structures. By investigating the interactions between risk factors, identifying less suspected contributors to dementia risk, and continuously experimenting to find optimal transfer learning combinations with suitable biomarkers, they should aim to advance the understanding of AD dementia [227,228].

Transfer learning can also be used to improve the prediction of atypical neurodevelopmental outcomes in very preterm infants. Incorporating different brain data sources, such as the brain structural connectome derived from diffusion MRI, can lead to more comprehensive and accurate predictions of neurodevelopmental deficits in preterm infants [229]. In addition, EEG signals for cognitive healthcare hold promising research scopes, such as exploring underutilized transfer learning algorithms, integrating with existing DL methods, investigating cross-category learning, addressing heterogeneous feature space tasks, and developing online transfer learning methods for real-time EEG analysis [230]. Transfer learning can be used in EEG-based BCIs to develop the detection and diagnosis of neurological disorders like migraine, pain, and depressive disorders. Researchers should focus on developing and refining transfer learning algorithms for specialized applications, such as migraine detection and pre-ictal migraine prediction [231]. Addressing these scopes can advance cognitive healthcare and brain-related applications through more accurate EEG signal analysis.

7.3. Explainable AI

XAI refers to a set of strategies and techniques that aim to make the decision-making process of AI models more transparent and understandable to humans. Understanding the decision-making process is very important for building trust, confidence, and ensuring responsible DL development in cognitive healthcare [232]. XAI holds significant potential in improving the accuracy and interpretability of brain imaging classification and diagnosis when dealing with dementia, such as AD. By using post hoc analysis and methods like Guided Backpropagation (GBP), Layer-wise Relevance Propagation (LRP), and DeepShap, researchers can gain insights into the features contributing to the prediction [233]. Moreover, involving humans in the process of using XAI models, conducting user experiments, and designing interactive tools can further improve the interpretability and usability of DL algorithms, making them more accessible and understandable to users [234].

XAI has been integrated into remote monitoring systems to support the early detection of cognitive decline in elderly individuals. Improving the performance of such systems by incorporating additional factors, reducing false positives through algorithm refinement, enhancing personalization, automating parameter tuning, and analyzing anomalies over extended periods should be prioritized in future research [235]. Further research should also focus on methodological improvements to achieve scalable, end-to-end systems with minimal human supervision. Besides, addressing ethical implications, conducting user-centered studies, and balancing transparency with predictive performance are crucial for the successful integration and acceptance of XAI in cognitive healthcare practice [236]. Apart from the physicians, XAI can also be valuable for non-task experts when reviewing medical scans and making decisions, leading to improved clinical outcomes and patient safety. Additional research should focus on improving the presentation of explainability to non-experts, ensuring its effectiveness while avoiding excessive reliance in situations where errors may occur [237].

7.4. Personalized cognitive healthcare

Personalized cognitive healthcare refers to the application of advanced ML techniques, particularly DL algorithms, to provide customized and individualized healthcare solutions for cognitive disorders. Training DL models with large datasets specific to cognitive health should be further prioritized for personalized diagnostic and therapeutic insights. Integrating wearables, mobile apps, voice assistants, and other technologies tailored to person-specific interfaces in intelligent systems, and combining DL-based identification of at-risk patients with effective notification and intervention strategies can lead to personalized care and early detection of cognitive decline [175]. Moreover, digital phenotypes can enable highly personalized and on-the-go treatments for mental illness, dynamically adapting recommendations based on an individual's health state and history at any given moment by leveraging DL, along with mobile sensing from smart devices [238]. Interdisciplinary collaboration is also crucial to realize the goal of personalized cognitive healthcare.

Much attention is required to develop more effective and personalized disease management approaches for dementia using EHR-derived data along with DL frameworks. Future research should consider identifying the potential risk factors and exploring the integration of multimodal data for personalized prediction of disease progression in individuals [239]. Integrating high-dimensional data in DL can identify alarming changes in cognitive state and behavior in individuals with MCI, enabling personalized risk assessment and early detection of cognitive decline. In addition to this, exploring the use of biomarkers derived from vital parameters can enhance predictive accuracy for AD and MCI in cognitive healthcare systems, improving outpatient management [240]. Finally, developing DL models that offer personalized predictor-outcome profiles, integrating additional biomarkers, real-time monitoring, and addressing data privacy and interpretability should be emphasized in order to optimize diagnostic procedures and improve the detection and management of cognitive disorders [241].

7.5. Longitudinal monitoring

DL techniques play an essential role in analyzing data to identify patterns and aid physicians in timely and accurate disease diagnosis. While considering a patient's symptoms, treatment plans, and medical history, DL assists physicians in comprehensively understanding patient health records. Processing longitudinal health data enables them to predict disease onset [242]. Although clinical data from local sources such as EHRs may have data quality issues, they offer valuable historical clinical information at the patient level. By employing DL techniques, these data can be effectively utilized to analyze the preclinical phase of AD, identifying prognostic clinical patterns [239]. Potential future research directions might consider conducting longitudinal analyses, where the evolution of a patient over time is assessed, including the prediction of disease progression rate and the significance of age as a determining factor [243].

7.6. Data security and privacy

DL-based applications raise challenges about data privacy and security, particularly in cognitive healthcare, where sensitive patient information is often targeted by data breaches [29]. To address such challenges, there is a need to explore and develop encryption schemes in order to prevent data leakage and ensure the reliability of the healthcare system. Moreover, strategies to balance the costs associated with secure multiparty computing, including disclosure, computation, and communication costs, require careful investigation to optimize efficiency. Future research should focus on the practical implementation of privacy-preserving DL frameworks, such as FL, to safeguard sensitive medical data in cognitive healthcare [244]. Future research should explore integrating novel technologies, adapting to privacy regulations and ensuring relevant and effective solutions. Adaptable frameworks, ethical considerations, user-centered design, and resilience against security threats aim to ensure the overall safety in cognitive healthcare systems [245].

7.7. Real-world validation and clinical adoption

DL in cognitive healthcare is still in its infancy, and most of the algorithms have not been thoroughly evaluated for their suitability in clinical settings, resulting in a lack of understanding of their practicality, acceptance, and effectiveness in clinical outcomes or services [246]. To ensure safe and effective clinical practice, researchers should focus on generating substantial scientific evidence that demonstrates the actual impacts of DL on patient outcomes and clinical care processes within real-world settings for cognitive healthcare. This entails close collaboration between the research community, healthcare providers, and institutions to establish a robust framework for validating DL applications in hospitals or healthcare centers. Through in-depth assessments of efficiency, safety, and benefits compared to existing standards of care, future research can pave the way for real-world validation and clinical adoption of DL technologies in cognitive healthcare, ultimately improving clinical decision-making and patient care outcomes [247,248].

Based on our review of recent research studies, we have further identified several promising avenues for exploration in DL, particularly in the context of cognitive healthcare. Key areas for advancement include enhancing real-time applications for health monitoring, optimizing sensor deployment for cognitive assessment, and refining training techniques for medical data analysis. Additionally, exploring diverse data modalities, achieving robust generalization across different healthcare datasets, and improving explainability for complex medical data are crucial for progress. In multi-modal learning, there are substantial opportunities for processing larger and video datasets related to cognitive health, innovating data augmentation methods, and advancing feature fusion strategies. Furthermore, emerging areas such as semi-supervised and unsupervised methods, reinforcement learning, graph neural networks, meta-learning, few-shot techniques, FL and split models remain largely underexplored in this domain. Each of these domains presents unique challenges and offers significant opportunities for innovation and advancement in improving cognitive health outcomes.

8. Conclusion

This review extensively explores the role of DL in cognitive healthcare. The potential of DL to advance patient care and our understanding of cognitive disorders effectively anticipates the future of cognitive healthcare. It has become a powerful and promising method in cognitive healthcare, transforming how we interpret data from wearable devices and revealing previously obscure mental health issues. When applied to cognitive health indicators like brain activity, heart rate, muscle activation, movement, and physical activity, DL provides a more comprehensive picture by integrating information from multiple signals (such as EEG, ECG, EMG, and accelerometry). DL has proven to yield impressive results when applied to various areas of cognition. Below are some noteworthy experimental findings uncovered by our review study.

(a) While reducing the computational burden of training the model, LSTM achieves perfect sensitivity at 100% and a mean specificity of 98.13% in the context of cognitive impairment.
(b) Additionally, the ensemble approach combining CNN and LSTM produces an impressive accuracy of 97.16% when applied to the development of an EEG-based emotion recognition system.
(c) DRNN accomplishes a significant 96% accuracy in predicting the stress levels of working pregnant women while also reducing the training time of the model.
(d) R-CNN attains an accuracy of 69.53% in predicting schizophrenia in children, although it faced challenges in achieving consistent performance across all individuals due to variations in how their brain activity patterns were categorized.
(e) ResNet-50 achieves a remarkable 99.59% accuracy and a 99.57% F1 score when classifying hand movements based on EMG signals.
(f) The preprocessing of data enhances signal quality and has the potential to enable models to reach a perfect 100% accuracy.
(g) In the context of cognitive impairment detection, GRU demonstrates an impressive 96.91% accuracy and can serve as a dependable biomarker for real-time monitoring.
(h) CNNs exhibit a favorable accuracy of 84.26% in detecting sleep disorders.

However, there are challenges to implementing DL in cognitive healthcare, such as the need for extensive and diverse datasets, difficulties in interpreting models, and ethical concerns about patient data privacy and security. DL architectures will be more widely applicable and usable in healthcare if they are adapted for low-powered devices. Large-scale clinical trials, explainable AI models, and integration of multi-modal data are all required to validate DL-based diagnostic and therapeutic approaches. However, there is still much to be done before DL techniques are widely adopted in low-cost cognitive healthcare systems. The role of DL in cognitive healthcare holds significant promise for the future of healthcare as a whole, with benefits including faster, more accurate diagnoses and more satisfying interactions between patients and doctors.

CRediT authorship contribution statement

Md. Sakib Bin Alam: Writing – original draft, Visualization, Formal analysis, Conceptualization. **Aiman Lameesa:** Writing – original draft, Visualization, Investigation. **Senzuti Sharmin:** Writing – original draft, Formal analysis. **Shaila Afrin:** Writing – original draft, Investigation. **Shams Forruque Ahmed:** Writing – review & editing, Supervision, Methodology, Conceptualization. **Mohammad Reza Nikoo:** Writing – review & editing, Software, Resources. **Amir H. Gandomi:** Writing – review & editing, Visualization, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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