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The Personal Health Applications of Machine Learning Techniques in the Internet of Behaviors

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Abstract: With the swift pace of the development of *artificial intelligence* (AI) in diverse spheres, the medical and healthcare fields are utilizing *machine learning* (ML) methodologies in numerous inventive ways. ML techniques have outstripped formerly state-of-the-art techniques in medical and healthcare practices, yielding faster and more precise outcomes. Healthcare practitioners are increasingly drawn to this technology in their initiatives relating to the *Internet of Behavior* (IoB). This area of research scrutinizes the rationales, approaches, and timing of human technology adoption, encompassing the domains of the Internet of Things (IoT), behavioral science, and edge analytics. The significance of ML in medical and healthcare applications based on the IoB stems from its ability to analyze and interpret copious amounts of complex data instantly, providing innovative perspectives that can enhance healthcare outcomes and boost the efficiency of IoB-based medical and healthcare procedures and thus aid in diagnoses, treatment protocols, and clinical decision making. As a result of the inadequacy of thorough inquiry into the employment of ML-based approaches in the context of using IoB for healthcare applications, we conducted a study on this subject matter, introducing a novel taxonomy that underscores the need to employ each ML method distinctively. With this objective in mind, we have classified the cutting-edge ML solutions for IoB-based healthcare challenges into five categories, which are *convolutional neural networks* (CNNs), *recurrent neural networks* (RNNs), *deep neural networks* (DNNs), *multilayer perceptions* (MLPs), and hybrid methods. In order to delve deeper, we conducted a *systematic literature review* (SLR) that examined critical factors, such as the primary concept, benefits, drawbacks, simulation environment, and datasets. Subsequently, we highlighted pioneering studies on ML methodologies for IoB-based medical issues. Moreover, several challenges related to the implementation of ML in healthcare and medicine have been tackled, thereby gradually fostering further research endeavors that can enhance IoB-based health and medical studies. Our findings indicated that Tensorflow was the most commonly utilized simulation setting, accounting for 24% of the proposed methodologies by researchers. Additionally, accuracy was deemed to be the most crucial parameter in the majority of the examined papers.

Keywords: health; artificial intelligence; machine learning; internet of behavior; medicine; IoT

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1. Introduction

The *Internet of Behavior* (IoB) applies devices to gather a huge amount of human behavioral information and change it into precious insights in order to develop a user's experience by altering their behaviors, preferences, and concerns [1,2]. With the increasing progress being made in efforts to use IoT devices to gather vast amounts of information, applying such devices to follow behavioral data in the IoB procedure will make the process simpler, quicker, and more effective [3,4]. The IoB attempts to adequately conceive data and utilize the perception obtained to build new results, support recent results, remodel the value chain, enhance benefits, or decrease costs [5,6]. So, the behavior of the user in the IoB workflow will first be followed when they utilize connected devices. The data produced by such devices will be gathered and evaluated by applying *machine learning* (ML) algorithms and data analytics [7,8]. The evaluation stage will generate suitable data, which should be appropriately understood from a behavioral science point of view [9,10]. So, the knowledge attained will be employed to improve business techniques and affect the user's behavior, thus gaining a particular target [11,12]. It follows and explores user behavior to identify and affect significant variables for the purpose of obtaining the objective of the process [13,14]. The IoB can become a strong marketing facility for businesses all around the world since it has the potential to provide them with in-detail personalized breakdowns of the perception of their users [15,16]. In terms of personal healthcare, the IoB can efficiently deliver customized services [17]. Also, the IoB can be used in health applications to offer behavioral corrections via efforts to conceive of the diet of the user, patterns of sleep, and levels of blood sugar [18]. Personalized healthcare can be a pivotal differentiator in providing quality services [19]. The IoB has significant potential to improve personal healthcare by enabling providers to quantify patient activity levels and examine the efficiency of healthcare activities. Indeed, this technology was used to monitor compliance with health protocols during the pandemic [20]. The IoB can also be used to track human activity and location to reduce the risk of viral contamination and identify unhealthy behaviors, allowing healthcare providers to intervene and prevent health problems. Additionally, the IoB can support the development of smart apps and devices that act as health advisors, providing users with real-time information on their health status and potential risks [21]. So, in order to conduct daily performances consisting of treatment arrangement and operations planning in healthcare, there is a requirement for the IoB [22]. The IoB aids in specifying the essential effective facets of a patient's behavior. Additionally, the IoB helps buyers to achieve their service demands without spending time directing different purchasing mechanisms for healthcare [23].

In addition, *artificial intelligence* (AI) is progressively enabling novelties, such as exploring the Internet via visual and audial detection, smart devices, and even driverless cars [24,25]. Previously, the primary constraints on AI consisted in the insufficiency of data available for training models, as well as the inadequacy of AI systems to manage data in their conventional format [26,27]. Today, with the ubiquitous digitalization of data about humans, algorithms of *deep learning* (DL) can progressively benefit from stockpiles of "big data" to increase a learning model's function and expand the complications and gains of AI application [28,29]. Machine learning algorithms are a subset of artificial intelligence that enable computers to learn from and adapt to data without explicit programming. They use statistical techniques to identify patterns and make data-driven predictions or decisions, refining their performance with experience [30]. On the other hand, artificial intelligence refers to the broader concept of creating machines or systems that exhibit human-like intelligence, including problem-solving, learning, reasoning, and decision-making capabilities. Machine learning serves as a crucial component of artificial intelligence, providing the tools and methodologies for systems to acquire knowledge and improve their performance, thereby propelling the advancement of intelligent technologies across various domains and applications. AI inventions are significantly ground-breaking in the area of healthcare services [31]. The applications of IoB and AI approaches have overshadowed the revolution in personal healthcare results for healthcare systems and humans. For example, numerous stockpiles of in-person health data are required for DL models [32]. Nowadays, personal health data like notes from regular visits to physicians, self-monitoring of paces, heartbeats, sleep, medical imaging, and DNA repositories are being quickly collected and used to train DL algorithms in a rising array of AI healthcare applications [33,34]. In fact, in comparison with profits from personal healthcare AI, much less regard has been paid to potential unintentional or inadvertent results of these improvements for humans and society [35].

In this study, we identified a deficiency in the organization of a coherent and disciplined taxonomy for the topic "Personal Health Applications Using Machine Learning Techniques in the Internet of Behaviors." To address this issue, we designed a novel and all-encompassing taxonomy that will provide readers with a coherent and easily comprehensible review paper related to this subject matter. Nonetheless, in the IoB–ML domain, there is no in-depth study of the ML/DL application. To provide an in-detail investigation of the novel systems presented by applying these technologies, the research is concentrated on the achievements, diagnosis, and detection of medical issues related to coping with such issues, forecasting death, and evaluating health equipment. The important contribution of this study is to map the most attractive areas of research, taking into consideration the current research into the various ML applications currently built for the diagnosis and treatment of healthcare problems. We have explored novel applications of ML methods within this subject and presented them in a well-defined structure to enhance readers' comprehension of this topic. The research adds a novel taxonomy of ML solutions for IoB-based healthcare, dividing these into five categories: convolutional neural networks (CNNs), recurrent neural networks (RNNs), deep neural networks (DNNs), multilayer perceptions (MLPs), and hybrid methods. Furthermore, we conducted a systematic literature review to (SLR) assess critical factors such as the main concept, benefits, drawbacks, simulation environment, and datasets, offering a structured review of the field. We discuss the use of high-quality and diverse datasets, which is crucial for the design of accurate and robust ML models. We considered incorporating a detailed discussion on data collection methods and data preprocessing. We beneficially elaborated on the criteria used to selecting the ML models in our research. Additionally, a thorough evaluation of the chosen models' performance metrics, including comparisons with other state-of-the-art models, would strengthen the validity of the findings. Given the sensitive nature of personal health data, our study addressed ethical considerations related to data privacy, consent, and potential biases introduced by the ML models. Laying out clear guidelines on the management of these ethical aspects throughout the research enhanced the paper's credibility. Discussing potential challenges and limitations in deploying ML-based personal health applications in real-world settings offered valuable insights to readers. Addressing scalability, security, and usability issues have provided a more comprehensive understanding of the feasibility and practicality of the proposed methodologies. Discussing case studies or real-world use cases of ML technique implementation in IoB-based health applications has provided tangible examples of the methodology's effectiveness and impact.

By considering these potential improvements, we have enhanced our paper's methodology section and contributed to advancing knowledge in the domain of personal health applications using machine learning techniques in the Internet of Behaviors. A *systematic literature review* (SLR) is employed in this study to explore, interpret, and integrate outcomes from the same studies. Furthermore, we categorize IoB-based ML/DL techniques used in healthcare into five main categories, namely *convolutional neural networks* (CNN), *recurrent neural networks* (RNN), *deep neural networks* (DNN), *multilayer perceptron networks* (MLP), and hybrid methods. We evaluated several criteria such as the benefits, drawbacks, main idea, simulation environment, and dataset for each class and technique applied to ML methods in healthcare. This paper provides data on the mechanisms and applications of ML methods in health and its topic encompasses a broad domain of illnesses that occur ubiquitously. In this paper, we looked into future work deeply, considering all the flows required to be mapped in the future. The main contributions of this paper are briefly listed below:

- Providing a comprehensive study of the existent challenges relevant to ML–IoB methods in healthcare;
- Providing a systematic review of the present techniques for the IoB-based ML method and other crucial actions;
- Describing significant methods in ML used to compose the IoB;
- Investigating each method that is referred to as an IoB-based ML method using different parameters like advantages, disadvantages, simulation environments, main idea, and dataset;
- Outlining pivotal zones that can develop the studied methods in the future.

This article is organized by the categorizations listed below. The next part addresses the essential concepts and terminology of ML methods in healthcare. The relevant studies review papers are mentioned in Section 3. The explored methods and tools for paper selection are provided in Section 4. Section 5 describes the classifications of the selected papers. Section 6 provides the outcomes and comparisons. Then, the open issues and conclusion are provided in Sections 7 and 8.

2. Fundamental Principles and Corresponding Terminologies

This section envelopes the concepts and terms related to using ML in the IoB.

2.1. *IoB Architecture, Definition, Usages*

The IoB refers to behavioral analysis data collected from the IoT and other datasets, and, afterward, efforts to make efficient utilization of them [36]. This information is collected through exclusive online activities, household electrical devices, and wearable technologies, which can give precious data about the intentions and behavior of users [37]. Tracking, collecting, integrating, and interpreting huge amounts of information provided by personal behavior and different online activities, consisting of commercial transactions and social media behaviors, is possible with the aid of both IoB and IoT methods [38]. Without any shadow of a doubt, data have been significant for businesses since the onset of the Internet. Although, in 2022, Gartner named the IoB as one of the most cutting-edge technological trends [39], the IoB still needs to allow everyone to gather and analyze data [40]. Moreover, behavioral data also aids businesses to make more noticeable decisions and develop their quality of service and chain of value feasibly [41]. The IoB process began with the essentials of IoT in terms of data streaming and data sharing [42]. The concept of the IoB involves a combination of technologies and disciplines, including behavioral psychology, behavioral analysis, usage data, IoT, products & services, and user experience. The IoB is a structure composed of several key components that work together to influence and shape human behavior [43]. These components include behavioral psychology, which provides insights into the factors that shape human behavior, such as motivation and social influence; behavioral analysis, which uses data and analytics to understand human behavior and develop personalized interventions; usage data, which are collected and analyzed from various sources such as social media, mobile apps, and IoT devices to identify patterns and trends; the IoT, which is the network of interconnected devices that collect and exchange data and is used by the IoB to collect data about individuals' behavior and provide personalized interventions; products and services that are developed to influence human behavior, such as mobile apps that encourage healthy habits and smart home systems that optimize energy usage based on individual behavior; and user experience, which aims to provide a seamless and intuitive user experience that encourages individuals to engage with technology and adopt desirable behaviors, incorporating elements of gamification to make behavioral change more engaging and enjoyable [44,45]. Figure 1 depicts the IoB structure, which is associated with several factors.

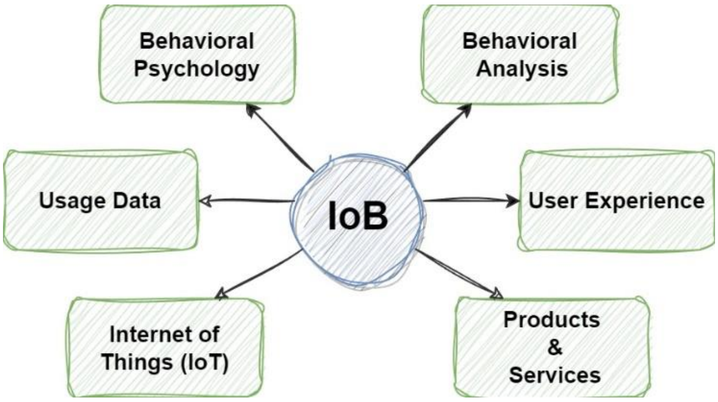

Figure 1. IoB structure including different components.

2.2. Various Features of IoB for the Healthcare Section

Figure 2 indicates the number of intelligent components of the IoB, exhibiting the power of the healthcare section. As mirrored in Figure 1, this concept contains the accurate stream health operations of data. These evolved with intelligent connection to process patients' information efficiently [46]. This flow is digital in its process and becomes faster, and finally results in strengthened patients. Figure 3 demonstrates the procedure and structure of the IoB for supporting and updating personal healthcare. Knowledge with improved wisdom is an integral section of this procedure and the stream of the IoB background. Regarding advanced technology, the IoB applies data collected by the IoT [47]. First of all, the IoB is employed to evaluate support operations. The IoB brings practical and comprehensible benefits. Cybercriminals can use behavioral data [48]. Consequently, businesses are required to attract more notice and be more proactive in protecting their data for several purposes [49]. The potential uses of these data include directing user experience models, providing services and products, helping businesses to make conscious decisions, and outfitting marketing methods [50]. Another component of the IoB is integrating and analyzing data from different sources to gain better and more effective decisions [51]. Combining the IoB and IoT should be considered ground-breaking technology and will become more functional in some areas [52]. Even though at an early phase, the potential and advantages of IoT solutions, while combined with IoB technology, are vivid. It may even produce an environment that specifies the behaviors and attitudes that manage the digital world [53].

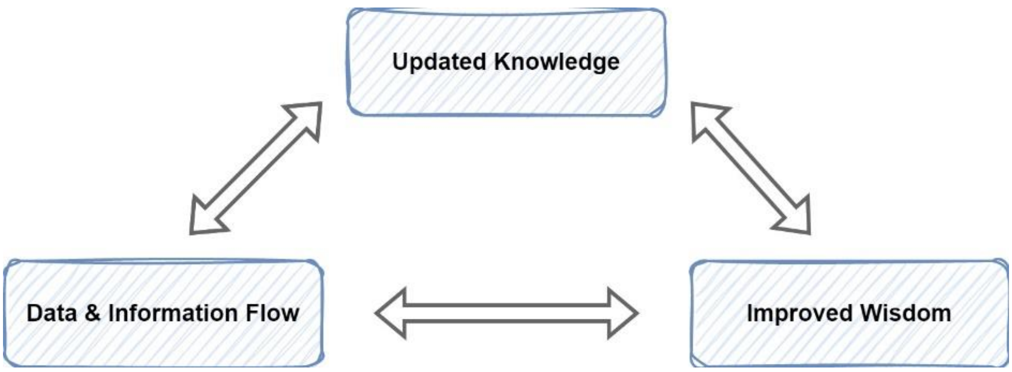

Figure 2. Smart component of the IoB examining the power of healthcare.

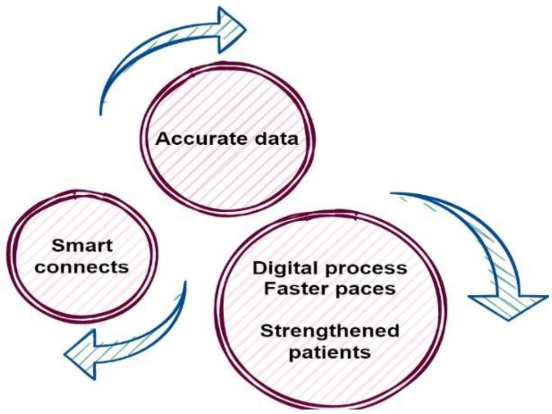

Figure 3. Stream health operations of data.

2.3. IoB Utilization for Healthcare Practices

The IoB provides predictive information on plans and objectives related to addressing pressing conditions in healthcare. The IoB turns into a tool for accurate prediction when it has particular users [54]. This works differently from the other apps that look to follow human motions, explore their locations, detect their gestures, and specify their vicinity to one another [55]. However, integrating these methods can generate a very strong and smart service at the same time [56]. The sophistication of the IoB is progressively rising and altering, consisting in how devices are communicated, what calculations they can conduct, and how information is hoarded in the cloud [57]. The transition to mobile devices has changed how humans interact with each other. The IoB devices' application data bring precious details on users' favored options, preferences, and performances [58]. In this way, behavior alternation apps could be suggested [59]. Also, the IoB has several applications in healthcare, including health monitoring, healthcare insurance, evaluating patients' activities, mask identification, illness supervision, fitness monitoring, healthcare improvement, examining physiology, evaluating health situations, and personalized medication and treatment [45]. IoB technology can be used to build health-monitoring smartphone apps that evaluate heart rates, food intake, sleep patterns, and blood sugar levels [60]. It can also be utilized to evaluate patients' activities and assess how healthcare activities work [61]. The IoB can help healthcare insurance by analyzing data from IoT devices to provide a more accurate estimate of insurance expenses. Computer vision businesses have also used the IoB to identify mask-wearing during the pandemic [62]. IoB technology can aid in illness supervision, car monitoring for insurance, fleet governance, and targeted purchasing offers. Fitness tracker data are being widely applied to develop the healthcare sector. The IoB can help physicians to offer better healthcare solutions to patients by using information from wearables [63]. It can also assist in understanding people's physiology and evaluating health situations. IoB devices can aid in personalized medicine and healthcare, leading to improved personalized treatment and medications [64].

3. Relevant Reviews on Personal Health Applications Utilizing Machine Learning Techniques in the Internet of Behaviors

We reviewed the background, perspectives, and definitions in the previous section. In this section, the initial goal is to review several current studies on personal healthcare applications utilizing ML/DL in the IoB. The main purpose of this section is to appropriately emphasize the significant consequences of recent research compared with what methods have been recently available. Regarding progress in AI technology, the application of AI methods in the IoB is ever-increasing. On the other hand, IoB-related challenges have roused the interest of academia. Additionally, the IoB is a hierarchical network management framework that has been modeled to direct IoB availability towards the aim personal healthcare. In this regard, Javaid and Haleem [65] studied the IoB and its requirements for healthcare. They investigated the features and structures of working in the healthcare area. Moreover, Pradhan and Elhadad [66] examined the current state of clinical narrative analysis, particularly efforts to recognize and normalize disorders. The authors evaluated various disorder recognition and normalization techniques in clinical narratives and identified their strengths and limitations. Their paper concluded by discussing the challenges that remain in this area of research and the need for the further development and evaluation of more advanced techniques.

Besides, Bose and Srinivasan [67] provided an overview of the recent techniques for *named entity recognition* (NER) and *relationship extraction* (RE) in a clinical text. Their paper began by discussing the challenges associated with NER and RE in the clinical domain, such as the presence of ambiguous and complex entities, different naming conventions, and the need for domain-specific ontologies. The paper then surveyed recent approaches for NER and RE, including rule-based, ML-based, and DL-based methods. Also, Konstantopoulos and Koumoulos [68] explored the use of digital innovation and ML strategies in the manufacturing of nanomaterials. They discussed how the combination of these technologies can lead to the development of more efficient and sustainable manufacturing processes. They also highlighted the importance of considering green perspectives in nanomaterial manufacturing, with a focus on reducing environmental impacts and promoting sustainability. Finally, Vettoretti and Cappon [69] presented a review of the current state-of-the-art techniques that employ AI and *continuous glucose monitoring* (CGM) sensors in the management of diabetes. The authors discussed various AI-based techniques that have been developed to improve diabetes management, including supervised learning, unsupervised learning, reinforcement learning, and DL.

However, there is a need for a new review article on DL–IoB in applications for personal health as prior studies have only given a general overview of DL applications in many domains. They have not completely examined the potential of DL to resolve the issues faced in the sector. Furthermore, recent improvements in DL algorithms have opened up new possibilities for enhancing the precision and effectiveness of personal health applications. We aid to highlight the areas that require further research and offer direction for future work in the field by offering a thorough assessment of the most recent advancements in DL and its applications in personal health applications. Table 1 shows relevant review papers studied concerning IoB-based ML methods for healthcare applications.

Table 1. Relevant work.

Authors	Main Idea	Advantage	Disadvantage
Javaid and Haleem [65]	Investigating IoB and its necessary for personal healthcare.	Touch on the topic theoretically in-detail.	Poor comparison between studied papers.
Pradhan and Elhadad [66]	Proposing the consequences from the 2013 ShARe/CLE shared task on disability entity detection and normalization.	Organizing cutting-edge evaluation of the clinical text.	Existence of discontinuous spans.
Bose and Srinivasan [67]	Stressing the present condition of clinical RE and NER and arguing the present proposed NLP models.	Consisting of recent issues, practices, and future directions in data extraction from clinical text.	Poor schematic comparison among studied papers.
Konstantopoulos and Koumoulos [68]	Providing a summary of improvement related to the raised effect in nonmaterial and nanoinformatics fields.	Enveloping recent issues towards decentralized, data-driven, unbiased decision-making.	Lack of access to a great deal of data.
Vettoretti, Cappon [69]	Reviewing the methodologies for applying CGM and AI sensors to decision support in T1D management.	Studying the most state-of-the-art methodologies and development trends.	Lack of support for the adoption of AI-based DSS applications in T1D management.
Our work	Reviewing IoB-based ML methods for personal healthcare applications.	In-detail evaluation of the topic.	Lack of evaluation of non-English resources.

4. Methodology of Research

We conducted an assessment of the literature about the utilization of ML in personal health applications within the IoB domain in the pervious section. In this section, we employed the SLR approach to gain a comprehensive understanding of the IoB field. The SLR technique entails a thorough examination of all research conducted on a particular subject matter. This segment culminates in an extensive analysis of the ML methodologies utilized within the IoB sphere, with a further examination of the reliability of the research selection methods used. The subsequent subsections provide additional information on the research methodologies employed, encompassing the selection metrics and research inquiries.

4.1. Question Formalization

The primary aims of the study entail identifying, assessing, and distinguishing all crucial documents in the field of ML applications for the IoB. To achieve these objectives, an SLR can be employed to scrutinize the elements and attributes of the methodologies. Additionally, the SLR facilitates the acquisition of profound insights into the critical difficulties and obstacles facing this industry. The subsequent paragraph enumerates various research queries.

RQ 1: How can ML techniques in the IoB areas be classified?

Section 5 includes this question's answer.

RQ 2: What techniques do researchers employ to conduct their investigation?

Section 5.1, Section 5.2, Section 5.3, Section 5.4 and Section 5.5 answer this question.

RQ 3: What parameters drew the most distinguished in the papers? What are the most trend ML applications used in the IoB?

Section 6 includes this question's answer.

RQ 4: What are the untouched future directions in this area?

Section 7 puts forward this question's answer.

4.2. Paper Selection Process

This research paper's search and selection strategies are grouped into four phases. Figure 4 explains these classifications. In the first phase, the keywords and phrases used to explore the articles are demonstrated in Table 2. An electronic database propels the finding of the articles. Also, chapters, journals, technical studies, conference papers, notes, and Special Issues were found. The first phase had a consequence of 625 papers being considered. The papers were analyzed using our standards. We selected papers in terms of several criteria, which are indicated in Figure 5. Figure 6 displays the distribution of publishers in the first step of choosing a paper.

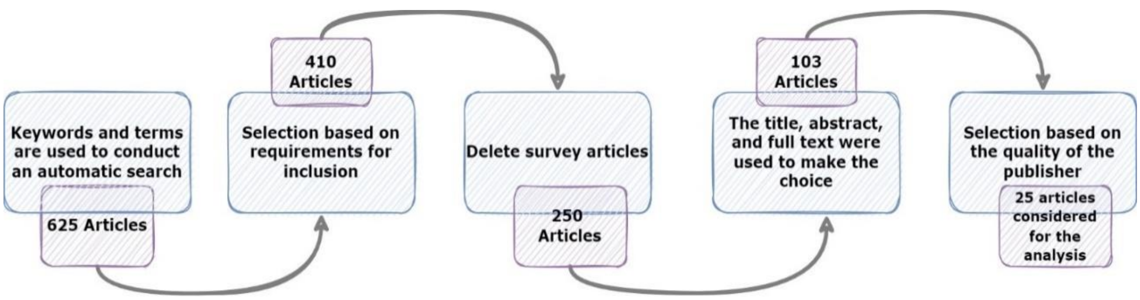

Figure 4. The steps of the paper exploring and selection procedure.

Table 2. Search keywords and terms.

S#	Keywords and Search Criteria
S1	"ML" and "Healthcare"
S2	"ML" and "IoB"
S3	"DL" and "ML"
S4	"IoB-based system" and "Bioinformatics"
S5	"AI" and "Medical issues"
S6	"DL" and "Personal Healthcare"
S7	"AI" and "IoB"
S8	"IoB" and "Healthcare"
S9	"AI" and "Healthcare"
S10	"DNN" and "Medical sector"

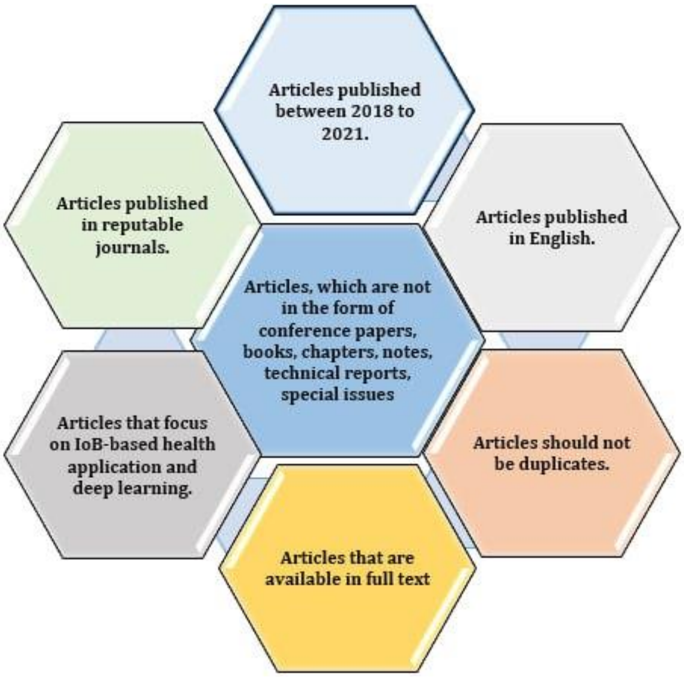

Figure 5. Metrics for involvement in the paper selection procedure.

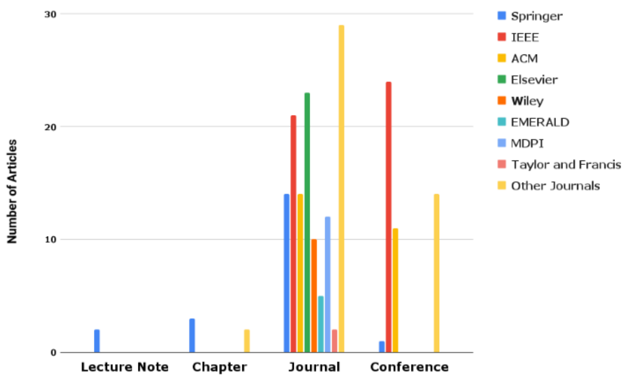

Figure 6. First phase of distributing papers by the publishers.

There were 410 recent articles left after initial exclusion, as the distribution of publishers in this phase demonstrates in Figure 7. Also, most of the research publications were published by IEEE. There were 250 papers left in the third phase, as indicated in Figure 8. The abstracts and titles of the articles were studied. The papers' discussion, methodology, analysis, and conclusion were investigated to make sure that they were related to the study. In the fourth step, 103 articles were chosen for the next review, as demonstrated in Figure 9.

Lastly, 25 articles were selected to investigate other publications as they fit the metrics. The following parts discuss ML–IoB methods and their properties in detail.

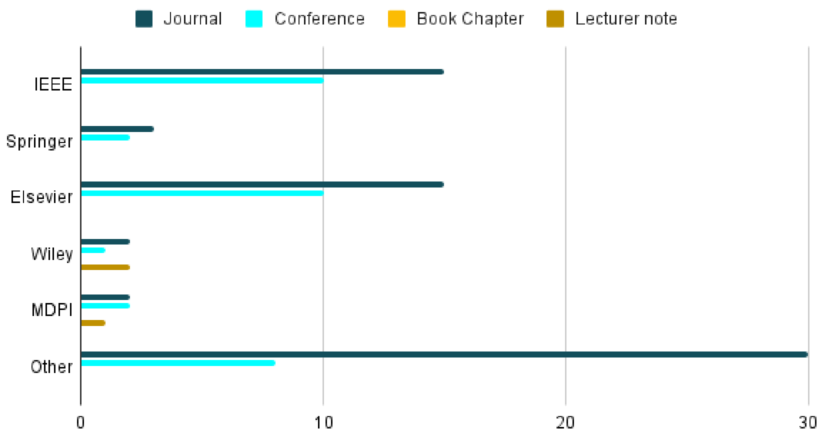

Figure 7. Second phase of paper distribution by the publishers (There are no chapters utilized).

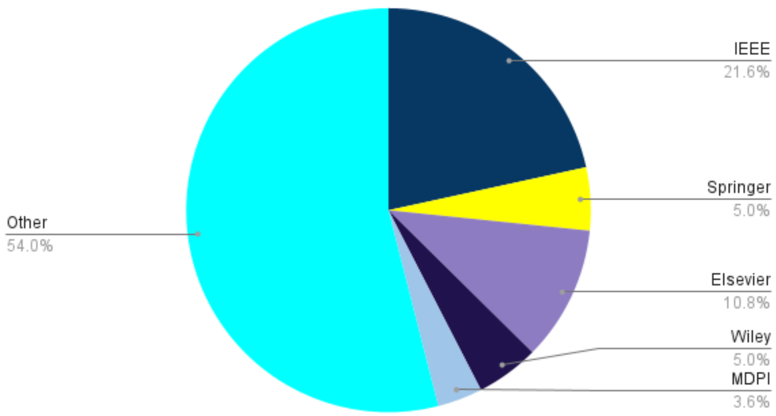

Figure 8. Third phase of paper distribution by the publishers.

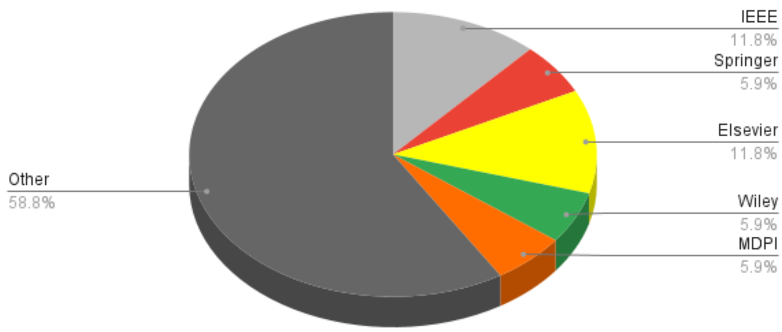

Figure 9. Fourth phase of papers' distribution by the publishers.

5. Health and Medical Applications Utilizing DL/ML Techniques Based on the IoB

In this section, we delved into the implementation of ML techniques in the field of the IoB for the monitoring of personal health. A total of 25 articles were included in this review, all of which fulfilled our selection criteria. The identified approaches were then categorized into five primary groups, namely CNNs, DNNs, RNNs, MLPs, and a variety of hybrid methods. A proposed taxonomy of ML–IoB applications in the domain of personal healthcare is illustrated in Figure 10.

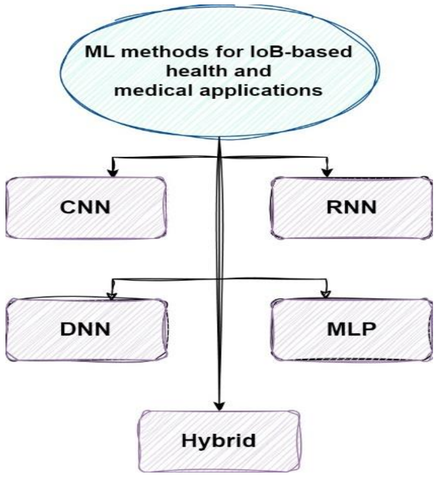

Figure 10. The proposed ML-based taxonomy for health applications.

5.1. CNN Methods

CNN is one of the DL approaches that can be applied in all terrains of healthcare and medicine and is one of the most practical techniques for investigators to use. This approach is prevalently utilized for personal healthcare applications and relevant backgrounds. We dwell deeply on five techniques in this section. The named entity recognition (NER) task is a foundation for progressive text evaluation. By the same token, in [70], a low-cost NER tool was proposed for use in biomedical text mining. The proposed tool, BINER, utilized rule-based and ML-based methods to identify and extract biomedical named entities from text. They evaluated the performance of BINER on three publicly available biomedical datasets and compared it with that of other state-of-the-art NER tools. Results showed that BINER performs competitively and with lower computational costs than other tools.

Besides, ref. [71] explored the emerging concept of the IoB and its implications for the development of explainable AI (XAI) systems in the context of IoT. They proposed a framework for designing IoB systems that take into account these challenges, as well as the need for effective user engagement and feedback mechanisms. They provided a comprehensive overview of the IoB and XAI systems and their potential for transforming the IoT landscape, while also highlighting the importance of ethical considerations and user-centric design.

Hasan, Roy [35] proposed a method to improve clinical relation extraction using a combination of traditional natural language processing (NLP) features and text embeddings. The proposed method used a neural network-based approach that combines both traditional NLP features, such as part-of-speech tags and dependency parsing, and text embeddings, which are vector representations of words or phrases that capture semantic meaning. They evaluated their method based on a publicly available dataset and achieved an improved performance compared to previous methods that used only traditional NLP features.

Moreover, Zhang and Zhao [72] proposed a method for identifying named entities in medical texts using a dilated CNN (DCNN). NER is a crucial task in NLP, especially in the medical field, where accurately identifying entities like drugs, diseases, and medical procedures is important. The proposed DCNN model used dilated convolutions to capture long-range dependencies between words in the input text, which helped to improve the model's performance. They trained and tested the model on the MedMentions dataset, which is a well-known benchmark dataset for medical NER tasks.

Also, Loh, Ooi [73] provided an eight-layer CNN for automated *major depressive disorder* (MDD) recognition. Spectrogram images were achieved by applying STFT (short-term Fourier transform) of electroencephalography EEG signals alongside the CNN model and they have gained the highest function with 10-fold cross-validation and hold-out validation. They described the development of a decision support system for detecting major depression using EEG signals. The system was trained and tested using a dataset of

EEG signals from patients diagnosed with major depression and healthy controls. Table 3 indicates methods using CNN for healthcare applications in the IoB.

Table 3. The methods, features, and properties of CNN-based healthcare techniques in IoB.

Authors	Main Idea	Advantages	Disadvantages	Method	Security Involved	Simulation Environment	Dataset
Asghari, M., et al. [70]	Proposing a model trained on low-tier GPU computers.	• Fewer layers needed • Improved F1-score	• Poor scalability • Poor flexibility	CNN	No	-	LINNAEUS JNLPBA
Elayan and Aloqaily [71]	Offering a reliable monitoring-evaluating-effecting behavior system utilizing IoB and XAI.	• Energy-efficient • Cost-efficient	• Lack of distributed version • High Complexity • Low speed of changing behavior process	CNN	No	Keras	An individual house-hold's electric power consumption
Hasan and Roy [27]	Investigating how various DL models and feature sets could be applied in connection extraction from text clinical.	• Outperforming two baselines on the similar dataset	• Underperforming contextual embedding learned by BERT while combined with other traditional NLP features.	CNN	No	Keras	2010 i2b2/VA
Zhang and Zhao [72]	Presenting a medical entity detection relying on dilated CNN.	• Improve the issue of low-speed training	• Poor scalability	CNN	No	-	Hospital-BJ CCKS-2017
Loh and Ooi [73]	Introducing an 8-layer CNN-based DL system for automated MDD recognition.	• Achieving higher function with both hold-out validation and cross-validation	• Utilizing only 64 subjects to improve the CAD model	CNN	Yes	Python	EEG

5.2. RNN Methods

The RNN technique finds dramatically widespread practical use in personal healthcare and IoB realms. As mentioned before, it is frequently used for forecasting and prediction approaches. We investigated five various methods in this part. In this regard, Lerner and Jouffroy [74] proposed a method for extracting medication information from clinical text using *RNN grammars* (RNNGs). They described how previous methods for medication information extraction have relied on manually crafted rules or statistical models. These have limitations such as the need for extensive domain knowledge and the inability to capture complex syntactic structures. They trained their RNNG model on a dataset of clinical notes from EHR and evaluated its performance against other state-of-the-art methods. The proposed model outperformed seq-BiLSTM for detecting complicated connections, with, on average, an 88.1% F-score. However, RNNG is interested in being weaker than baseline BiLSTM in recognizing entities, with an average of 82.4% F-score.

In addition, Peng and Rios [75] presented a method for automatically extracting information on chemical–protein interactions from the scientific literature using a combination of ML techniques. The authors first compiled a dataset of abstracts from scientific articles that mention both chemicals and proteins and manually annotated them to indicate the type of interaction between the two. They then used this dataset to train and test two different types of ML models: *support vector machines* (SVMs) and DL models. The SVMs were trained on a variety of different features extracted from the text, including lexical, syntactic, and semantic features. On the other hand, the DL models were trained on raw-word embeddings using a CNN architecture. Their approach showed promise in terms of automatically extracting information on chemical–protein interactions from the scientific literature and could be applied to other types of information extraction tasks.

Additionally, Jouffroy and Feldman [76] proposed a method for extracting medication information from French clinical texts using a combination of expert knowledge and DL. They developed a system called MedExt, which combined expert knowledge from a medical terminologist and a pharmacist with DL techniques. The MedExt system consisted of two main components: a rule-based component for identifying medication-related entities and a DL component for classifying the identified entities. The authors trained their DL model on a small, annotated dataset of French clinical texts and evaluated its performance on a larger dataset of unannotated texts. The authors found that the MedExt system accurately identified and classified medication-related entities into medication categories.

Moreover, Zhao and Cui [77] presented a method for learning brain networks using deep RNNs that can capture temporal dependencies. They proposed a supervised learning framework that uses RNNs to learn the functional connectivity patterns in the brain. The method was applied to *functional magnetic resonance imaging* (fMRI) data to predict the functional connectivity between brain regions. The authors used a dataset of 200 subjects from the Human Connectome Project and compared their method with several other state-of-the-art methods for learning brain networks. The results showed that the proposed method performs better than the other techniques in terms of accuracy and robustness. The authors also showed that the learned brain networks can be used to identify meaningful connections between brain regions that are related to specific cognitive tasks.

Also, Frank and Iob [9] looked into how depression symptoms changed among at-risk populations in the UK during the COVID-19 epidemic. They conducted a longitudinal study using data from the UK Household Longitudinal Study. This included a sample of vulnerable individuals such as those with pre-existing mental health conditions, low-income individuals, and those with disabilities. The authors analyzed data from three waves of the study, conducted between April and June 2020, and measured depressive symptoms using the *Center for Epidemiologic Studies Depression Scale* (CES-D). They found that depressive symptoms increased among vulnerable groups during the COVID-19 pandemic. They also identified different trajectories of depressive symptoms among vulnerable groups, including a stable high-symptom trajectory and an increasing symptom trajectory. Table 4 outlines methods that use RNN for healthcare applications in the IoB.

Table 4. The methods, features, and properties of RNN-based healthcare techniques in IoB.

Authors	Main Idea	Advantages	Disadvantages	Method	Security Involved	Simulation Environment	Dataset
Lerner and Jouffroy [74]	Evaluating RNNG model for healthcare data extraction in clinical texts.	• High adapt-ability • High accuracy	• Poor scalability	RNN	Yes	Python	APmed
Peng and Rios [75]	Defining submission in the BioCreative VI CHEMPROT task.	• High accuracy	• Poor scalability • Poor adaptability	RNN	No	-	2432 PubMed abstracts
Jouffroy and Feldman [76]	Improving a hybrid system combining contextual word embedding and an expert rule-based system.	• High F-score	• Poor diversity • Poor scalability	RNN	No	Python	320 clinical texts and 19,957 sentences with 173,796 words

Table 4. *Cont.*

Authors	Main Idea	Advantages	Disadvantages	Method	Security Involved	Simulation Environment	Dataset
Zhao and Cui [77]	Proposing a hybrid framework, supervised brain network training.	• High robustness • High reliability	• Poor adaptability	RNN	No	Tensorflow	HCP tfMRI
Frank and Iob [9]	Examining trajectories of depressive symptoms over time.	• High accuracy	• Poor adaptability	RNN	No	-	51,417 adults

5.3. DNN Methods

DNNs are a strong class of ML algorithms that are implemented by stacking layers of neural networks along the width and depth of smaller models. DNNs have currently indicated representative and distinctive learning abilities over a broad domain of applications. So, Yepes and MacKinlay [78] proposed a method for the supervised learning of brain networks using deep RNNs. Brain networks are complex structures that represent the connectivity between different regions of the brain. The authors aimed to develop a method with which to accurately classify brain network states based on the connectivity patterns between brain regions. The proposed method consisted of two parts: a feature extraction stage and a classification stage. In the feature extraction stage, the authors used a deep RNN method to learn the temporal dependencies of the brain network data. This stage involved training the RNN on a set of input brain network data and using its hidden states as features for subsequent classification. In the classification stage, a linear SVM is used to classify brain network states based on the learned features. The authors evaluated the proposed method on two datasets, namely, the *Human Connectome Project* (HCP) dataset and the *Autism Brain Imaging Data Exchange* (ABIDE) dataset. The results showed that the proposed method outperformed others in terms of classification accuracy. Furthermore, the authors performed a feature analysis to show that the learned features were able to capture important information about brain network connectivity.

Also, Jouffroy and Feldman [76] aimed to develop an algorithm for extracting medication-related information from clinical texts in French using a hybrid DL approach. They trained and tested their algorithm using a dataset of clinical texts in French containing medication information. They evaluated the performance of their algorithm using standard metrics such as precision, recall, and F1 score. The results showed that their algorithm accurately identified medication-related information from clinical texts in French, with an F1 score of 0.942.

Cao and Qian [73] also put forward a *bidirectional LSTM* (Bi-LSTM) recurrent network that could be applied in two regularizations to solve the short-note categorization issue. To begin with, they adjusted the familiar attention technique to aim the network training, utilizing the range of knowledge in the directory when a knowledge dictionary was not accessible. Moreover, they proposed a multi-task system in order to train the range knowledge dictionary to address the cases and classify the texts at the same time. The authors applied their approach to a real-world interactive medical system and a broadly publicly accessible ATIS dataset. According to the results, the proposed model could positively obtain the note's critical point and outperform several baselines.

In addition, Silvestri and Gargiulo [79] proposed a method for iteratively annotating biomedical NER corpora using DNN and knowledge bases. NER is the task of identifying and classifying named entities, such as genes, proteins, and diseases, in biomedical texts. Their proposed method first used a pre-existing NER system to annotate a small portion of the corpus automatically. Human annotators then reviewed the annotations, and any errors were corrected. The corrected annotations were used to train a DNN to perform NER on the remaining unannotated text. The neural network output was further reviewed and corrected by human annotators, and the process was repeated until all the text was annotated. They also proposed using external knowledge bases, such as the *Unified Medical Language System* (UMLS), to improve the accuracy of the annotations.

Additionally, Chalapathy and Borzeshi undertook research on this issue [80]. The paper proposed a model for extracting clinical concepts from EHR using a bidirectional LSTM model combined with a *conditional random field* (CRF) layer. The proposed model outperformed existing methods on two benchmark datasets used for clinical concept extraction. The authors also conducted experiments to individually show the effectiveness of the bidirectional LSTM and CRF layers. They concluded that the proposed model can accurately extract clinical concepts from EHRs, which can improve the efficiency of clinical decision-making processes. Table 5 indicates methods using DNN for healthcare applications in the IoB.

Table 5. The methods, features, and properties of DNN-based healthcare techniques in IoB.

Authors	Main Idea	Advantages	Disadvantages	Method	Security Involved	Simulation Environment	Dataset
Yepes and MacKinlay [78]	Proposing a method to operate annotation of medical things applying a tracking neural network.	• High F-score • High accuracy • High recall	• Poor design of the structure	DNN	No	PyTorch	Micromed
Jouffroy and Feldman [76]	Improving a hybrid model composing a contextual and an expert law-based model.	• High precision • High Recall • High F-score	• Poor scalability • Poor diversity	DNN	No	Python	320 clinical texts
Cao and Qian [81]	Presenting a BiLSTM recurrent network to solve the short-note classification.	• High accuracy	• Poor flexibility	DNN	No	-	ATIS COHCP
Silvestri and Gargiulo [79]	Putting forward a method that relies on active training.	• Developed response time	• Poor flexibility	DNN	No	-	Word2vec
Chalapathy and Borzeshi [80]	Discussing the efficiency of the contemporary bidirectional LSTM-CRF clinical concept extraction.	• Capability to create end-to-end detection utilizing general-purpose data	• Lack of applying unsupervised word embedding trained from domain-specific resources	DNN	No	-	2010 i2b2/VA

5.4. MLP Methods

MLP is a connected multi-layer neural network. It has at least 3 layers consisting of one hidden layer. An MLP is a common feedforward artificial neural network (ANN) instance. Stylianou and Vlahavas [82] proposed a method for evidence-based medicine and argument mining in medical literature using end-to-end transformers. Evidence-based medicine is the practice of making clinical decisions based on the best available evidence, and argument mining is the task of identifying and extracting arguments from texts. Their method used a pre-trained transformer-based language model, BERT, as a feature extractor for medical text. The extracted features were then fed into a neural network that was trained on a task-specific dataset for evidence-based medicine or argument mining. They evaluated their method on two publicly available datasets and achieved improved performances compared to previous methods that used either rule-based or ML approaches. They also performed an ablation study to investigate the contribution of the transformer-based feature extractor and found that it significantly improved the performance of the system.

Additionally, Vehí and Contreras [83] discussed the use of ML techniques to predict and prevent hypoglycemic events in type-1 diabetic patients. They used data collected from CGM devices and insulin pumps worn by patients to train and validate their ML models. They used various ML algorithms, including decision trees, logistic regression, and SVM, to predict the occurrence of hypoglycemic events in advance. The study also proposed a method to prevent hypoglycemic events using an AI algorithm that adjusts the insulin doses administered to the patient. The algorithm used real-time data from the glucose-monitoring device to calculate the appropriate insulin dose required to maintain glucose levels within the normal range and prevent hypoglycemia. The results of their study demonstrated the effectiveness of the ML models in predicting hypoglycemic events with high accuracy.

Also, Roberts [84] investigated the trade-off between corpus size and similarity in word embeddings for clinical NLP. They evaluated the performance of word embeddings trained on clinical text data of varying sizes and compared it to word embeddings trained on non-clinical text data. They also investigated the effect of different similarity metrics on the performance of word embeddings. The results showed that word embeddings trained on clinical text data outperformed those trained on non-clinical text data. The authors also found that increasing the size of the clinical text data improved the performance of the word embeddings, but only up to a certain point, after which the performance plateaued.

Additionally, Yüksel [85] described the use of DL approaches to extract protein–ligand interactions from the biomedical literature. They noted that identifying protein–ligand interactions is crucial for drug discovery and development. However, this task is challenging due to the vast amount of biomedical literature and the complexity of NLP. They employed two DL approaches to overcome these challenges: a CNN and an LSTM network. These models were trained on a dataset of annotated sentences that mention protein–ligand interactions. The results showed that both models perform well in identifying protein–ligand interactions from the biomedical literature, with the LSTM network achieving higher levels of accuracy.

Moreover, Grivas and Alex [86] compared the performance of rule-based and neural network-based information extraction systems for use in brain radiology reports. Information extraction is the task of automatically identifying and extracting relevant information from text. They evaluated the performance of two rule-based systems and one neural network-based system on a dataset of brain radiology reports. They compared the systems' performance on two information extraction tasks: identifying the presence of a stroke and identifying the stroke type. The results showed that the neural network-based system outperformed the rules-based systems on both tasks, achieving higher precision, recall, and F1-score. They also performed an error analysis to investigate the reasons for the performance differences between the systems. Table 6 indicates methods using MLP for healthcare applications in the IoB.

Table 6. The methods, features, and properties of MLP-based healthcare techniques in IoB.

Authors	Main Idea	Advantages	Disadvantages	Method	Security Involved	Simulation Environment	Dataset
Stylianou and Vlahavas [82]	Presenting an end-to-end transformer pipeline to attain a better function.	• Low latency • High availability	• Poor scalability	MLP	No	-	EBM-NLP

Table 6. *Cont.*

Authors	Main Idea	Advantages	Disadvantages	Method	Security Involved	Simulation Environment	Dataset
Vehí and Contreras [83]	Proposing the application of four ML algorithms to deal with the issue of security in diabetes aim.	• High robustness • High flexibility	• Poor adaptability	MLP	Yes	MATLAB	Adaptive synthetic sampling
Roberts [84]	Introducing a series of tests to analyze the trade-off between small-representative and large- corpora.	• High safety	• Poor scalability	MLP	No	Tensorflow	I2b2
Yüksel [85]	Analyzing the influence of linguistic features.	• High accuracy • High F-score	• Poor cost-efficiency	MLP	No	Tensorflow	BindingCreative
Grivas and Alex [86]	Comparing three clinical data extraction systems to operate entity detection.	• High Recall	• Limited size • Poor scalability • Poor availability	MLP	No	Python	AIS

5.5. Hybrid Methods

One of the more complex approaches used in personal healthcare is the hybrid approach. This technique is the combination of two or more methods for coping with issues. In these analyses, we determined the studied methods that were created by applying that methodology. We found that these techniques are usually utilized in a diverse topic relevant to our topic. In this section, we investigate five various techniques. Rabee [87] proposed an efficient early breast cancer diagnosis approach. The non-ionizing method applied in their study implemented antennas that diagnosed the tumor while operating under the frequency domain of the IoB and Wi-Fi, which means the device cannot be applied at home. This strategy utilized an exclusive feature extraction method under *ultra-wideband* (UWB) microwave conditions and two different kinds of breast model to build patient datasets. Their paper formulated acceptable information for a machine smart system applying the UWB-implemented antenna. Many applicable supervised methods for ML, such as decision trees, SVM, and closest-neighbor, were studied by applying this information. Applied SVM delivered a great accuracy of conclusions, at 93%.

Also, Peng and Lu [88] proposed a DL approach for extracting *protein–protein interactions* (PPIs) from the biomedical literature. PPIs are important for understanding the biological mechanisms underlying diseases and drug targets. The authors developed a CNN model that takes the text of biomedical articles as the input and outputs the probability of a PPI between two proteins. Their model was trained on a dataset of PPIs extracted from the BioGRID database and evaluated on two benchmark datasets. They also performed an ablation study to investigate the contribution of different components of the model to its performance. The findings had important implications for the development of more accurate and efficient methods of extracting PPIs from large-scale biomedical data.

One critical phase in improving EEG-specific patient cohort retrieval systems is the annotation of a large corpus of EEG reports. The annotation of numerous types of EEG-specific medical implications, alongside their modality and polarity, is problematic, particularly when automatically conducted on big data. To address this issue, Iob and Pingault [89] aimed to investigate the causal relationships between physical activity, sedentary behavior, and mental health/substance use disorders using a method called Mendelian randomization. Their study used data from large-scale genetic studies and EHR to identify genetic variants associated with physical activity, sedentary behavior, and mental health/substance use disorders. They then used these variants to perform Mendelian randomization analyses in order to determine whether physical activity and sedentary behavior causally influence mental health and substance use conditions. The study's results suggested that higher levels of physical activity may have a protective effect against depression, anxiety, and substance use disorders, while higher levels of sedentary behavior may increase the risk of depression and anxiety.

Also, Gao and Thamilarasu [90] addressed the issue of security in connected medical devices, which have become increasingly prevalent in healthcare environments. They proposed the use of ML classifiers to enhance the security of these devices. They argued that traditional security measures, such as firewalls and intrusion detection systems, are not sufficient to protect against increasingly sophisticated attacks. Instead, they proposed using ML algorithms to detect anomalous behavior and identify potential security threats. Their paper presented a framework for building ML classifiers for security in connected medical devices. Their framework included four stages: data collection, feature extraction, classification, and evaluation. The authors evaluated their framework using a network traffic dataset from a simulated medical environment.

Additionally, Phan and Dou [91] proposed a DL approach to predict human behavior in health social networks, specifically targeting the prediction of depression risk in patients. The proposed model was based on a *social restricted Boltzmann machine* (SRBM) that was trained on various types of data, including social interactions, demographic information, and electronic medical records. Their model incorporated an explanation mechanism to provide reasons for its predictions, which can be useful for healthcare professionals in understanding and interpreting the model's output. The authors demonstrated the efficiency of the proposed approach through experiments on a real-world dataset of depression patients, achieving significant improvements over existing methods in terms of prediction accuracy and interpretability. Table 7 indicates methods using hybrid methods for healthcare applications in the IoB.

Table 7. The methods, features, and properties of hybrid-based healthcare techniques in IoB.

Authors	Main Idea	Advantages	Disadvantages	Method	Security Involved	Simulation Environment	Dataset
Rabee [87]	Proposing an efficient early cancer diagnosis method.	• High accuracy	• Poor flexibility	SVM/DT/NN	No	-	PCA datasets
Peng and Lu [88]	Putting forward a multichannel dependency-based CNN model.	• High F-1 score	• Poor scalability	CNN/DNN	No	Tensorflow	PPI corpora, AIMed, and BioInfer
Iob and Pingault [89]	Presenting a new active learning annotation framework.	• High accuracy	• Poor adaptability	LSTM/SVM	No	Python	Temple University Hospital dataset
Gao and Thamilarasu [90]	Examining the viability of applying ML to identify security attacks.	• High security	• Limited feature set	SVM/Decision tree/K-means	No	Castalia	1000, 4000, and 7000 sample size
Phan and Dou [91]	Introducing SRBM+ for human behavior anticipation.	• High accuracy • High stability	• Poor comparison between discussed methods	Decision tree/nearest	No	-	2766 inbox messages

6. Results and Comparisons

We looked in depth at DL/ML-based IoB-based health and medical applications in the previous section. This section thoroughly reviews the findings and examines the methodologies from many angles. Considering personal healthcare, applications that applying ML/DL in the IoB are storming ahead at a ground-breaking pace ahead in medical and healthcare fiels. A detailed analysis revealed that most health ML applications in the IoB focus on advanced datasets, combined learning tasks and annotation protocols. However, there are several limitations to achieving the same level of function in healthcare ML applications. One of the most critical limitations is the shortage of large datasets for use in training. Additionally, standardized data collection is essential to ensuring that the various types of data, which require larger and more diverse datasets to produce reliable outcomes, have adequate access to them necessary resources. For detection, virtually all proposed methods applied CNN or CNN-based techniques. The authors evaluated the topic based on several attributes, such as accuracy, F-score, robustness, precision, recall, adaptability, and flexibility. Sections 5.1–5.5 illustrate healthcare ML applications in the IoB. According to the findings, most proposed methods are used to benchmark real-time data, and various datasets are used in terms of numbers and categories. Most settled frameworks consider parameters such as accuracy, robustness, flexibility, adaptability, scalability, F-score, and precision, with accuracy being the main parameter for healthcare-based systems and robustness being the least applied parameter. Data normalization was found to be the main technique used to create images from numerous sources of similar quality and size. However, as different datasets were used for examination, the computing time was not demonstrated in many of the provided systems. The datasets employed in the research had various features, such as the number of data, accessibility conditions, samples, image size, and classes, with most not recognizing contributors and image sizes differing significantly. The SVM algorithm is one of the most commonly used, with cross-validation rarely used in most research. This may decrease the resiliency of the outcomes, as it is not clear how the test data vary. It is worth mentioning that cross-validation is pivotal for evaluating entire datasets. However, multiple studies use ML-based methodologies, and it is challenging to establish clear, robust, and resilient models. Future tasks should focus on minimizing false-positive and false-negative rates to enhance the dependability of methods for assessing phenomena such as viral and bacterial pneumonia. The association of ML methods in the IoB for developing personal health applications is a ground-breaking pace forward in technological development.

As previously mentioned, CNN is a type of ML algorithm that can efficiently process vast amounts of data, making it widely used in medical and healthcare applications. One of the main advantages of CNN over other ML methods is its ability to extract features without the need for human intervention or significant segmentation. This attribute enables CNN to discover the intrinsic characteristics of the data being analyzed, which in turn enhances the algorithm's effectiveness. Moreover, CNN's computational efficiency is achieved through its use of specific convolution, parameter sharing, and pooling techniques. These are particularly advantageous for use in image classification algorithms as they can work with fewer features and understand abstract properties. However, when employing CNN for model training, overfitting, class imbalance, and explosive gradients may pose challenges that must be addressed. On the other hand, the RNN method, as elaborated in the preceding section, presents a range of parameters that can provide more benefit to high-precision analytical systems than CNN. RNN-based performances can enhance system accuracy, although gradient-exploding problems and difficulty evaluating long sequences can be significant drawbacks. In contrast, MLP exhibits a lower level of complexity when updating weights, which is beneficial for the model's overall performance. This approach's advantage lies in the fact that each weight update requires less computational power, resulting in an O (1) complexity. Additionally, MLP can be more robust in terms of handling randomness during weight initialization, although longer training times and increased memory requirements may be necessary. Finally, implementing dropout in MLP may be more challenging than in other models due to its sensitivity to various random weight initializations.

6.1. Analysis of Results

We studied five categories and 25 papers in the prior sections about healthcare applications of ML techniques in the IoB, as shown in Figure 11. Besides, Tensorflow is the most frequently used programming language for the simulation of, implementation of, or theoretical setting of the presented frameworks. This method is very practical for researchers to utilize more and more in future work and has a broad range of applications. According to Figure 12, Python is the first choice for proposed methods, with a 24 percent rate of use. Keras, PyTorch, and MATLAB are the other most prevalent methods. Also, Figure 13 indicates a geographical map of countries under study, with more investigation concentrating on predicting, processing, and other applications in the US (6 papers), the UK (4 papers), and China (3 papers). These countries contribute the greatest amount of research on this issue. Also, Figure 14 shows the evaluated parameters in the studied papers.

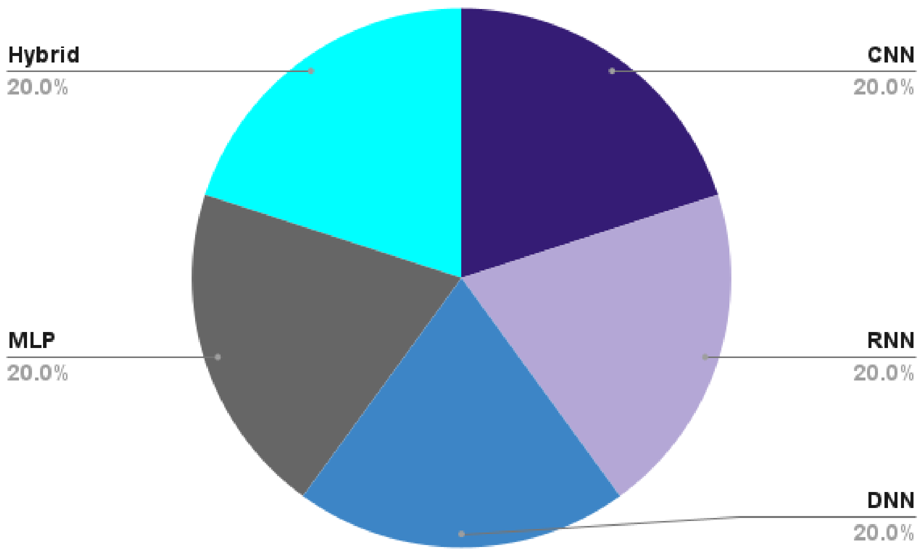

Figure 11. The frequency of methods used for IoB-based healthcare applications.

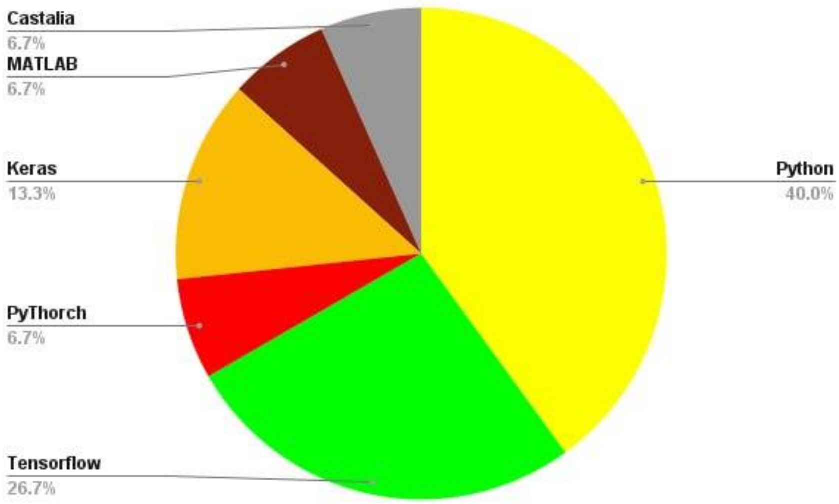

Figure 12. The distribution of the various simulation environments in ML-healthcare.

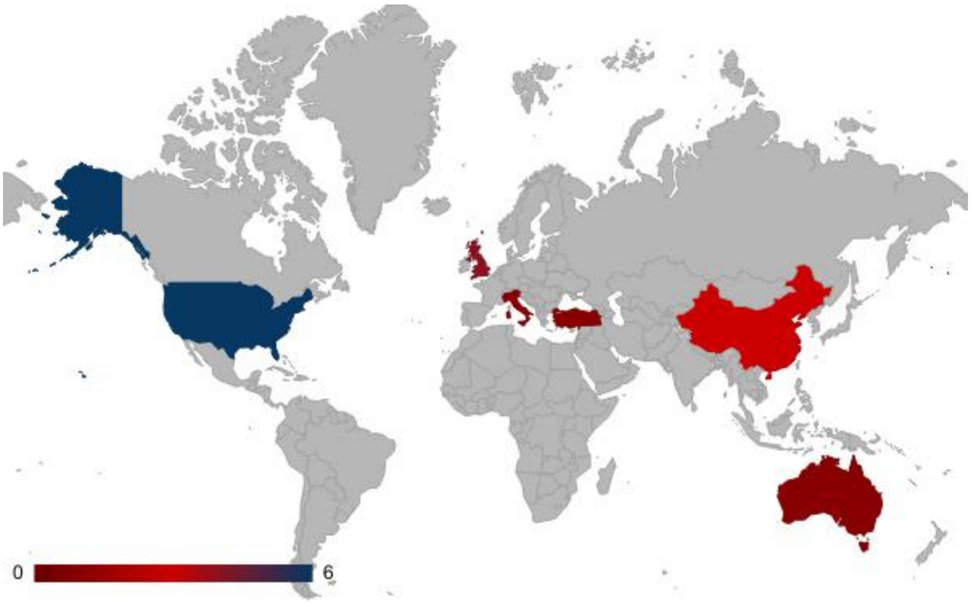

Figure 13. The geo-chart of the studied countries by the selected articles.

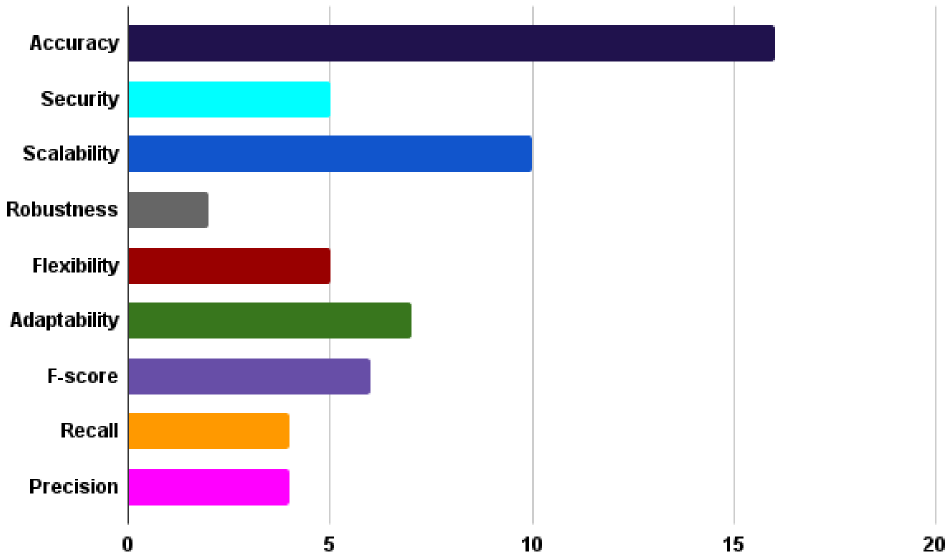

Figure 14. Evaluated parameters in studied papers.

The concept of the IoB endeavors to accurately assess factual information and utilize that perception to enhance and introduce innovative components from the perspective of human psychology. It aims to tackle concerns regarding the evaluation of information and utilize such data to generate and propose novel services, with each task resolved on the basis of human psychology. This novel trend has the potential to influence the development of quality infrastructure as many enterprises may augment their communication via these methods and thus elevate consumer demands. As illustrated in Figure 15, the IoT can convert information into data, while the IoB can convert our knowledge into genuine wisdom.

As previously mentioned, the CNN architecture is a type of ML algorithm that can efficiently process vast amounts of data, making it widely used in medical and healthcare applications. One of the main advantages of CNN over other ML methods is its ability to extract features without the need for human intervention or significant segmentation. This attribute enables CNN to discover the intrinsic characteristics of the data being analyzed, which in turn enhances the algorithm's effectiveness. Moreover, CNN's computational efficiency is achieved through its use of specific convolution, parameter sharing, and pooling techniques, which are particularly advantageous for image classification algorithms as they can work with fewer features and understand abstract properties. However, when employing CNN for model training, overfitting, class imbalance, and explosive gradients may pose challenges that need to be addressed. On the other hand, the RNN method, as elaborated in the preceding section, presents a broad range of parameters, which can prove more beneficial for high-precision analytical systems than CNN. RNN-based performances can enhance system accuracy, although gradient-exploding problems and a difficulty evaluating long sequences can be significant drawbacks.

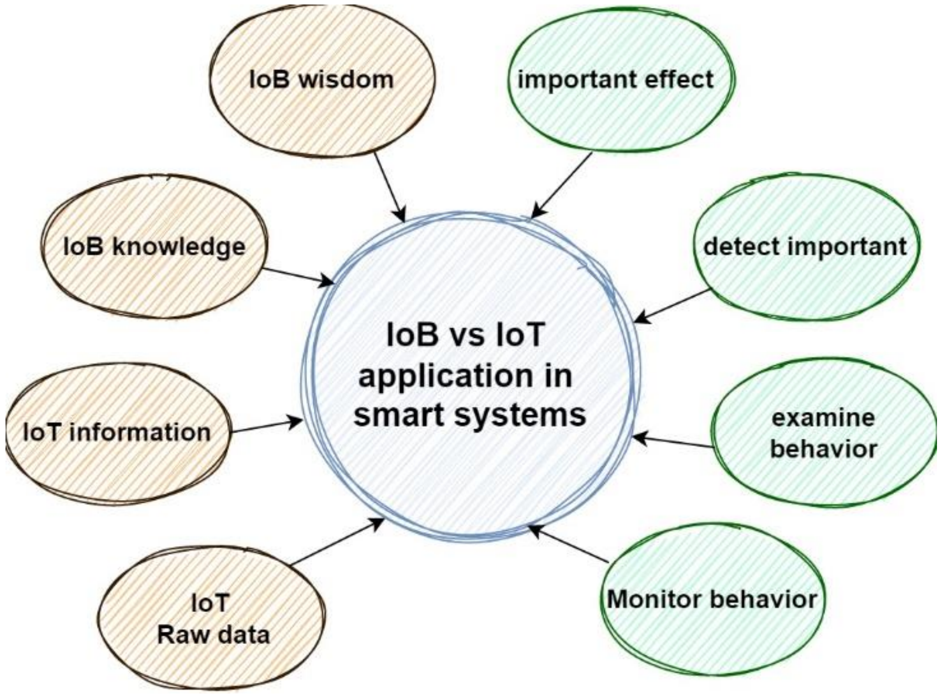

Figure 15. IoB vs. IoT application in smart systems.

In contrast, MLP exhibits a lower level of complexity when updating weights, which is beneficial for the model's overall performance. This approach's advantage lies in the fact that each weight update requires less computational power, resulting in an O (1) complexity. Additionally, MLP can be more robust in terms of handling randomness during weight initialization, although longer training times and increased memory requirements may be necessary. Finally, implementing dropout in MLP may be more challenging than in other models due to its sensitivity to various random weight initializations.

6.2. Prevalent Evaluation Criteria

One of the well-known evaluation criteria is the F-score. The mentioned keys are applied to calculate the recall, F-score, and precision. It is worth mentioning that *true positive* (TP) means sick people are truly recognized as sick. *False positive* (FP) also means that healthy people are wrongly recognized as sick. Also, *true negative* (TN) means healthy people are truly recognized as healthy. Furthermore, *false negative* (FN) means sick people are wrongly recognized as healhty. Precision demonstrates the number of true results truly recognized; meanwhile, recall indicates the entire entities recognized. These concepts are calculated as follows [92]:

$$\text{Precision} = \frac{\text{STP}}{\text{STP} + \text{SFP}} * 100 \tag{1}$$

$$\text{Recall} = \frac{\text{STP}}{\text{STP} + \text{SFN}} * 100 \quad (2)$$

$$\text{F1-score} = \frac{2 * \text{Recall} * \text{P}}{\text{Recall} + \text{P}} * 100 \quad (3)$$

$$\text{Accuracy} = \frac{\text{STN} + \text{STP}}{\text{STP} + \text{STN} + \text{SFN} + \text{SFP}} * 100 \quad (4)$$

Furthermore, AI techniques are adept at deciphering paradigms from linear data. This is pivotal in augmenting the precision of detection, which depends on evolving psychiatric signs. Moreover, AI strategies may have an ascending role in gathering precise and sensitive data from patients. One research discovered that individuals were more likely to disclose vulnerable data to a computer system than to a human being. AI techniques are geared towards the digital health movement, utilizing data beyond customary physician–patient interactions. Daily and linear monitoring of sensors and social media allows the early diagnosis of signs or the detection of their worsening and highlights beneficial versus detrimental behaviors. Multimodal sensing encompasses smartphones, physiological sensors, heart rate, wearable devices, and surrounding sensors, facilitating the harvesting of real-world, extended data on signs, behaviors, thoughts, treatment responses, and emotions. Platforms modeled to permit multimodal data collection, such as CrossCheck, mindLAMP, and AWARE, aid in the continual remote monitoring and detection of objective or subjective indicators of psychotic worsening. ML methods can extract new features from inherently noisy signals generated by sensors. Fitbit data and smartphones can identify behaviors such as social withdrawal.

Social media platforms have represented a novel form of social relations, mirroring the daily performance of many people. Thus, they present a new, unobtrusive "lens" into linear moods and behaviors, especially for youth and adolescents, who are the most frequent internet users and face the most significant challenge in terms of the need for mental health care. Analyzing social media consumption paradigms, language, and content generates new perspectives into connections and relationships and creates novel opportunities for seeking help. Web-based effects impact an individual's understanding and approach toward healthcare operations at personal and population levels. Mental illnesses may be detectable on online platforms and the capacity of social media information to be used to forecast identifications and recurrences has been validated, with accuracies comparable to those of clinician assessment and screening tests.

However, sensor data still lack vivid applicability in clinical mental health adjustments due to a lack of clinical credibility and implementation issues. Additionally, evaluations of social media information necessitate AI-based inventions and joint infrastructures for data dedication and collection. Furthermore, the significant security-related and ethical considerations concerning social media information and public distrust of data utilization for sensitive goals may hinder research and the building of the large-scale datasets required for AI algorithms. Table 8 illustrates the parameters considered in the examined articles. Most scholars consider accuracy as the most significant parameter and it occurs most frequently amongst those considered in the papers studied. Furthermore, scalability, adaptability, and F-score are other frequent parameters considered for evaluation in the articles studied. However, as a limitation, most scholars focused on only one or two metrics in their research, with the others overlooked.

Table 8. Considered parameters in the examined articles.

	Authors	Accuracy	Security	Scalability	Robustness	Flexibility	Adaptability	F-score	Recall	Precision
CNN	Asghari and Sierra-Sosa [70]	•	•	✔	•	✔	•	✔	•	•
	Elayan and Aloqaily [71]	✔	•	•	•	•	•	•	•	•
	Hasan and Roy [27]	✔	•	•	•	•	•	•	•	•
	Zhang and Zhao [72]	✔	•	•	•	•	•	•	•	✔
	Loh and Ooi [73]	✔	•	✔	•	•	•	•	•	✔
RNN	Lerner and Jouffroy [74]	✔	•	•	•	•	✔	•	•	•
	Peng and Rios [75]	✔	•	✔	•	•	•	✔	•	•
	Jouffroy and Feldman [76]	•	✔	✔	✔	•	•	•	•	•
	Zhao and Cui [77]	✔	•	•	•	•	•	•	•	•
	Frank and Iob [9]	✔	•	✔	•	•	✔	✔	✔	•
DNN	Yepes and MacKinlay [78]	•	•	•	•	•	✔	✔	✔	✔
	Jouffroy and Feldman [76]	✔	✔	•	•	•	✔	•	•	•
	Cao and Qian [81]	✔	•	✔	•	•	•	•	•	•
	Silvestria and Gargiulo [79]	✔	•	•	•	✔	•	•	•	•
	Chalapathy and Borzeshi [80]	•	✔	•	•	✔	•	•	•	✔
MLP	Stylianou and Vlahavas [82]	•	•	✔	✔	✔	•	•	•	✔
	Vehí and Contreras [83]	•	✔	•	•	•	✔	•	•	•
	Roberts [84]	✔	•	✔	•	•	•	✔	✔	•
	Yüksel [85]	•	•	•	•	•	•	•	✔	•
	Grivas and Alex [86]	✔	•	✔	•	•	•	•	•	•
Hybrid	Rabee [87]	•	•	•	•	✔	•	✔	•	•
	Peng and Lu [88]	✔	•	✔	•	•	•	•	•	✔
	Iob and Pingault [89]	✔	•	•	•	•	✔	•	•	•
	Gao and Thamilarasu [90]	•	✔	•	•	•	•	•	•	•
	Phan and Dou [91]	✔	•	•	•	•	✔	•	•	✔

✔, it signifies that the referred parameters have indeed been thoroughly evaluated and discussed in the paper by the authors. •, it indicates that the mentioned parameters have not been evaluated in the paper.

6.3. Healthcare Practices Using ML Methods

In this section, we dwell deeply on healthcare applications using ML methods. Although ML has found use in numerous areas, we mention two healthcare applications that directly take broad advantage of AI techniques.

6.3.1. Prognosis Applications

The utilization of AI techniques for longitudinal data can enhance the accuracy of psychiatric patient prognoses. Research studies have utilized various forms of data such as neuroimaging, genetics, speech, and EHR, to establish patterns of depression, surgical outcomes, and suicidal tendencies. Furthermore, AI algorithms can utilize data-driven methods to develop innovative clinical risk-forecast models that are not reliant on conventional theories of psychopathology. Nevertheless, the internal and external validity of AI algorithms is critical for their clinical implementation. While cross-validation is a crucial step for basic internal validation, these measures do not ensure the generalizability of the outcomes. Transient and geographical validation techniques are more stringent methods for ensuring clinical applicability.

6.3.2. Therapy Applications

AI technologies have the potential to facilitate psychiatric treatment across multiple avenues. Firstly, AI can be employed to predict treatment responses, circumvent lengthy psychotherapies and expensive brain stimulation treatments, and streamline inefficient medication trials. Studies have forecasted responses to antidepressant medications using clinical questionnaires and EEG signals, responses to *electroconvulsive therapy* (ECT) based on brain structure, responses to brain stimulation based on MRI, and responses to *cognitive behavioral therapy* (CBT) for anxiety based on brain fMRI. Such investigations can identify objective populations for different treatments, though not all investigations yield positive results. Secondly, AI methods can map and predict the severe impacts of therapies. One study applied EHR data to forecast the improvement of renal insufficiency in patients treated with lithium. Furthermore, AI methods can assist in developing novel theoretical frameworks of illness pathophysiology. Another study examined advanced deviations of neuroimaging abnormalities in bipolar patients, supporting the theory of bipolar disorder as an advanced neuro illness. Additionally, identifying the timing of events and brain regions that change during the transition from psychosis prodrome to schizophrenia could aid in understanding risk and provide reliable markers for use during the prodromal stage. These methods could identify opportunities for early intervention, although detecting the most heavily weighted risk factors for transitioning to diseases is necessary. Moreover, ML methods could assist in identifying gene expression patterns characteristic of diverse psychiatric disorders. Also, another study provided data on a system that can accurately predict which patient will develop *post-traumatic stress disorder* (PTSD) based on pre-arrangement blood transcriptome data, emphasizing immune-related gene dysregulation as a risk factor. Lastly, AI could aid in the exploration of novel treatments directly. AI approaches could help to predict the clinical behavior of drugs through simulation or data-driven techniques, thus exploring new combinations with therapeutic potential.

6.4. Healthcare Subdomains Use AI Methods

Recently, automated medical image detection has disputably become the most prosperous area of healthcare AI usage. Numerous healthcare specialties, consisting of radiology, ophthalmology, dermatology, and pathology, depend on image-based detection. In the following sections, we looked into current progress in the use of AI in each of these healthcare areas.

6.4.1. Radiology Applications

Diagnostic radiologists use a variety of healthcare imaging modalities. The most broadly used to diagnose and identify illnesses were MRI, X-ray radiology, positron-emission tomography, and computed tomography [93]. Radiologists use sets of images for disease screening, identifying the disease's cause, and monitoring patient progress. Images often include a large amount of the data necessary to achieve an accurate diagnosis. Since radiological diagnosis relies heavily on imaging for detection, it is closely associated with DL methods such as [94]. Many radiology departments maintain a database of images in an image archiving and communication system, which often provides numerous examples with which to train neural networks. Computational methods for radiological diagnosis have been proposed and implemented since the 1960s. With the latest ML techniques, several AI-based radiology practices have achieved professional-level diagnostic accuracies via methods such as diagnosing lung nodules using computed tomography images, detecting pulmonary tuberculosis and other lung diseases with chest radiology, and performing breast mass detection using mammography scans [95]. These researchers used transfer learning, in which well-trained DNNs are fine-tuned on a large number of biomedical images, reducing the number of training examples necessary to train a neural network with a large number of parameters [41]. Several clinical applications of AI are seeking regulatory approval, such as the FDA-approved DL system for detecting cardiovascular diseases using cardiac MRI images. With more validation studies and technology transfer efforts, the use of *computer-aided detection* (CAD) and diagnostic systems that rely on images will increase in clinical applications soon [96].

6.4.2. Dermatology Applications

Several different kinds of skin lesions may be detected with the use of an audit. The visual features of common melanoma, for instance, set it apart from benign tumors. Dermatologists created audit rules, such as the well-known ABCDE legislation, for the diagnosis of skin melanoma [97]. Measures A (geometric asymmetry), B (abnormal borders), C (color variety), D (diameter equal to or more than a certain size), and E (extension of the lesion surface or growing lesion) are used in the method to detect pigmented tumors [98]. Researchers have been working on automatic diagnostic systems that can distinguish between malignant and benign tumors in images for quite some time [99]. When comparing algorithm predictions to dermoscopy pictures, the DL algorithms fared better than the average dermatologist. Even though the DL model's training phase might be computationally intensive, the final diagnostic model is set up on a mobile device, expanding access to medical-grade skin lesion detection [100].

6.4.3. Ophthalmology Applications

Non-invasive fundus photography is used to diagnose and monitor conditions such as glaucoma, neoplasms, and diabetic retinopathy by photographing the macula, retina, and optic disc using specialized cameras [101]. The use of fundus imaging is crucial in determining the root causes of avoidable blindness. The *American Diabetes Association* (ADA) advises annual screening for *Diabetic Retinopathy* (DR) in individuals with minimal or mild DR and more frequent screening for people with advanced DR [102]. Section 5 reveals that, similar to ophthalmologists, the ML model achieved ranges under the receiver performance feature curve greater than 0.990 in two separate assessment datasets. Investigators also discovered that DL can uncover unnoticed connections between retinal image paradigms and demographic variables such as age, systolic blood pressure, smoking history, gender, and the presence of severe cardiovascular disease [103].

6.4.4. Pathology Applications

Histopathological evaluation stands as the gold standard for detecting various types of cancer. This method involves slicing a surgical specimen or biopsy into tissue slides and staining them with pigments. Pathologists then interpret the slides under a microscope using visual assessment. While differences among pathologists have been noted, the procedures are not easily scalable [104]. Furthermore, certain quantitative image properties in histopathology, which are not easily discernible to the human eye, can predict patient survival, highlighting the presence of untapped data in pathology slides. With the emergence of deep CNN, AI can aid in diagnosing prostate cancer through biopsy specimens and detecting breast cancer metastasis in lymph nodes [105]. For example, ML, in conjunction with live-cell biomarkers, can reduce the risk stratification of breast and prostate cancer patients. We predict that, by 2030, there will be a shortage of over 5,700 pathologists of the same caliber, a problem that could be mitigated by automated systems that enable quick and objective analysis of histopathology slides, thereby enhancing the quality of cancer patient care [106].

6.4.5. Interpretation of Genome Applications

Data in the terabyte range can be produced using high-throughput sequencing methods. Understanding inter-individual differences and facilitating precise treatment relies on the correct clinical interpretation of such data. Unfortunately, in light of the rapidly developing field of human genome science, human curation makes it impossible to systematically compare frequent cases with patients' genomes and individual controls [107]. Working more accurately than attempts with other CNN approaches like logistic regression and SVM, DNNs can annotate harmful variations and diagnose the performance of non-coding DNA. A neural network that was trained using an approach which transforms genomic variant calling into picture categorization outperformed the popular genome analysis toolkit. Cancer is a genetically complicated illness, and these computational approaches can help to detect it [108].

6.4.6. ML Applications in Biomarker Exploration

The discovery of biomarkers requires researchers to find associations between various traits and measures that were not previously known to exist. High-throughput measurements of a plethora of proteins, genes, and epigenomic and genomic aberrations have been made possible by omics technology [109]. Nevertheless, it is not feasible for researchers to manually evaluate and analyze the massive amounts of data obtained via omics approaches [110]. When forecasting the phenotypes of diseases, ML methods may be used to detect molecular paradigms linked to disease states and subtypes, to account for the high-level interconnections between measurements, and to extract omics signatures. Cancer, Down's syndrome risk, and infectious illness may all be predicted by analyzing DNA methylation, gene expression, and protein profiles [111]. When compared to biomarker panels picked by specialists or using standard statistical methods, those retrieved using ML often perform far better. The Food and Drug Administration has validated the reliability of certain panels from these for routine use in guiding treatment choice [112]. The creation of a user interface for prosthetic inspections can be facilitated using non-omics biomarkers such as brain signals. The use of successfully developed data-extracted biomarkers for trial design and clinical testing is of great importance.

6.4.7. Clinical Result Anticipation and Patient Checking

There is great potential in using EHR to predict clinical outcomes and in discovering biomarkers associated with clinical features [113]. Predictions of mortality, remission, and length of hospital stay may be made via Bayesian networks using ED EHR data. Clinical forecasters for the prognosis of patients undergoing organ transplantation can be identified using data from health insurance declarations. Patient characteristics in healthcare notes can be used to classify cancer patients with varying responses to chemotherapy [114]. Clinical predictors of patients' outcomes have been established through these types of studies, which may help patients and doctors to decide on the best course of therapy. A clinician's demeanor and speed of decision-making may be assessed in a matter of seconds, making patient monitoring essential in ERs, ICUs, cardiology wards, and operating theatres. These notes contain regular monitoring devices that generate massive quantities of data, making them a perfect candidate for artificial intelligence-assisted alarm systems [115]. A cardiac arrest prediction algorithm based on vital signs has been created. Cardiac arrest, intensive care unit admission, and mortality can all be predicted based on laboratory results, patient characteristics, and severe symptoms. In addition, an ML model that is easy to understand might help anesthesiologists to anticipate cases of hypoxemia. This demonstrates that DL algorithms can improve the use of raw patient monitoring data, allowing for more precise clinical prediction and prompt decision-making, while avoiding data overload and alert overload.

6.4.8. Inferring Personal Health Conditions by Wearable Devices

Novel wearable devices can record various biomedical signals, including heart rate, limb tremor, and voice, which can be beneficial for diagnosing illnesses and inferring health conditions. Wearables can identify symptoms of infectious diseases and inflammatory responses by utilizing body temperature and heart rate information. Photoplethysmography sensors can be integrated into wearables in order track cardiovascular diseases, pulmonary illnesses, sleep apnea, and anemia. Wearables can also diagnose and quantify signs of patients with Parkinson's disease, such as tremors, gait difficulties, hand motion, speech pattern, and posture. However, the precision of the information gathered through wearables can vary, and personal monitoring devices present an opportunity to target behavioral changes. Despite their potential benefits, one-third of all American users who have owned wearable devices ceased using them after six months. Thus, more research is needed to maximize the efficiency of wearables in promoting healthcare. Overall, the successful application of DL in healthcare relies on the availability of large, labeled information, DL techniques, and computational power to achieve expert-level detection precision. However, applying DL methods to personal healthcare is not a straightforward process as it has the potential to alter existing healthcare practices. The method uses behavioral data to facilitate personalized patient care and digital healthcare within the I–fog–cloud network [116]. Also, incorporating advanced deep learning vision-computing techniques within a cognitive cloud framework, this research contributes to the intersection of AI, ML, and IoT in waste management, promoting a healthier environment and sustainable practices [117].

6.5. Generative AI

A notable recent development in the field of artificial intelligence is generative AI. Generative AI, specifically in the form of generative models, has emerged as a powerful technology that holds promising potential for use in personal health applications. Generative models, such as GANs and VAEs, can learn and mimic the underlying data distribution, enabling them to generate new and realistic data samples [118]. In the realm of healthcare, generative AI can play a transformative role by augmenting the diversity and volume of behavioral data within the Internet of Behaviors. These generative models can be leveraged to create synthetic but realistic behavioral patterns, which could be used to enhance the training of machine learning algorithms in personal health applications [119]. For instance, they could be employed to augment the limited datasets or generate additional scenarios for training and validation purposes. Furthermore, generative AI opens up new avenues for creating personalized health interventions and treatment plans. By understanding individual behavioral patterns, these models can be used to generate tailored recommendations and interventions that align with users' unique needs and preferences within the Internet of Behaviors [120]. However, as with any emerging technology, there are challenges to be addressed. Ethical considerations, such as ensuring the responsible and transparent use of generated data, as well as potential biases introduced by the generative models, must be carefully managed to avoid unintended consequences in personal health applications. Incorporating an analysis of generative AI in this area would provide valuable insights into the cutting-edge advancements in and possibilities for enhancing healthcare outcomes through the synthesis and personalization of behavioral data. This exploration can guide researchers and developers in harnessing the full potential of generative AI to create more impactful and personalized health applications within the Internet of Behaviors [121].

6.6. An Analysis of UI–UX Design of Healthcare Products

In this area, analyzing the UI–UX (user interface–user experience) of healthcare products is a crucial aspect that warrants attention. The UI–UX design plays a pivotal role in determining the overall usability, user satisfaction, and effectiveness of these applications, especially when dealing with personal health data and behavioral insights. A comprehensive UI–UX analysis would involve evaluating various aspects of the healthcare products, such as:

- ➢ User-Friendliness: Assessing how intuitive and easy-to-navigate the user interface is and ensuring that individuals can seamlessly interact with the application without any confusion or steep learning curves.
- ➢ Data Visualization: Analyzing the visual representation of health-related data and insights and ensuring that the presented information is clear, concise, and easily interpretable for users, regardless of their technical expertise.
- ➢ Personalization: Evaluating the level of personalization and customization options available to users, allowing them to tailor its application to their specific health goals and preferences.
- ➢ Data Privacy and Security: Examining the UI–UX elements related to data privacy and security, such as user consent mechanisms, information encryption, and clear communication on how personal data is utilized and protected.
- ➢ Feedback and Engagement: Analyzing how the application provides feedback to users on their behaviors and health progress, as well as evaluating the presence of motivational features that promote user engagement and adherence to health recommendations.
- ➢ Accessibility: Assessing the inclusivity of the UI–UX design and ensuring that the application is accessible to users with different abilities, including those with visual or motor impairments.
- ➢ Error Handling and Recovery: Examining how the application handles errors and providing users with clear guidance on rectifying mistakes and recovering from any unexpected issues during usage.
- ➢ Integration with IoB Devices: Evaluating the seamless integration of IoT devices within the UI–UX and ensuring that data from wearable devices and sensors are accurately displayed and used to provide meaningful health insights.

The analysis of UI–UX in healthcare products can be conducted through a combination of user testing, surveys, and heuristic evaluations, involving both healthcare professionals and potential end-users. The findings from this analysis can guide iterative improvements to the UI–UX design, leading to more user-centric and effective personal health applications that leverage machine learning techniques within the Internet of Behaviors. A well-designed and user-friendly UI–UX can foster greater user engagement, adherence to health interventions, and overall satisfaction with the application, ultimately enhancing the positive impact on individuals' health and well-being.

6.7. An Analysis of Digital Treatments

Analyzing digital treatments is a crucial aspect of this process that merits investigation. Digital treatments refer to the implementation of technology-based interventions, such as mobile apps, virtual reality, or online platforms, in order address health-related issues and promote behavioral change. The analysis of digital treatments in this area involves evaluating various aspects, including:

- ❖ Effectiveness: Assessing the effectiveness of digital treatments powered by machine learning techniques in achieving their intended health outcomes. This involves analyzing research studies, clinical trials, and real-world data to determine the impact of these treatments on individuals' health behaviors and well-being.
- ❖ Personalization: Examining the level of personalization offered by digital treatments, where machine learning algorithms can tailor interventions based on individual preferences, health status, and behavioral patterns within the Internet of Behaviors.
- ❖ Adherence and Engagement: Evaluating the level of user adherence and engagement with digital treatments over time. Analyzing user behavior and interactions with the application can provide insights into the factors that contribute to sustained engagement and those that may hinder user participation.
- ❖ Usability and User Experience: Conducting a UX analysis of the digital treatments to determine how user-friendly and intuitive the applications are. This includes

evaluating the navigation, design elements, and overall user experience to ensure a positive and satisfying interaction.

- ❖ Integration with IoB Data: Investigating how digital treatments leverage data from IoT devices within the Internet of Behaviors to provide personalized feedback and interventions. Understanding the seamless integration of these data sources is crucial for effective and contextually relevant treatment delivery.
- ❖ Long-term Effects and Sustainability: Analyzing the long-term effects of digital treatments on users' health behaviors and their potential to sustain positive changes over extended periods. This involves exploring whether the effects persist beyond the initial intervention phase and contribute to lasting improvements in health outcomes.
- ❖ Data Privacy and Security: Examining the data privacy and security measures implemented in digital treatments to protect users' personal health information. Addressing potential concerns regarding data breaches and unauthorized access is essential for building user trust.
- ❖ Integration with Healthcare Systems: Investigating the potential integration of digital treatments with existing healthcare systems to enable seamless communication and coordination between patients, healthcare providers, and digital interventions.

The analysis of digital treatments in this context can provide valuable insights into the efficacy, usability, and overall impact of machine learning-powered personal health applications. Understanding the strengths and limitations of these digital treatments can inform the development of more effective and user-centric interventions within the Internet of Behaviors, ultimately contributing to improved health outcomes and the empowerment of individuals to manage their health and well-being.

6.8. Medical Device Certification

In this subject, the topic of medical device certification, particularly concerning regulatory bodies like the U.S. Food and Drug Administration (FDA), becomes relevant and crucial. When incorporating machine learning techniques in personal health applications, especially those operating within the Internet of Behaviors, it is essential to consider the necessary certifications and approvals to ensure the safety and efficacy of these medical devices [122]. The FDA plays a significant role in regulating medical devices in the United States. Any personal health application that meets the definition of a medical device and utilizes machine learning techniques would likely fall under the FDA's purview. Therefore, adherence to FDA regulations, including obtaining the appropriate certification or clearance, becomes imperative before these applications can be legally marketed and distributed for medical purposes. Medical device certification by the FDA involves a rigorous evaluation process to assess the device's safety and effectiveness, as well as its compliance with relevant regulations. This evaluation considers the specific intended use, indications, and potential risks associated with the device [123]. The FDA may require the submission of clinical data, performance testing, and the validation of the machine learning algorithms to ensure that the device meets the necessary standards. As personal health applications continue to evolve and integrate machine learning techniques to harness behavioral data from the Internet of Behaviors, the need for appropriate medical device certification becomes increasingly critical. By adhering to the regulatory guidelines and obtaining the necessary certifications, developers, and researchers can instill confidence in users, healthcare professionals, and stakeholders about the reliability and safety of these AI-powered healthcare solutions. So, addressing the importance of medical device certification is crucial, particularly concerning regulatory bodies like the FDA. This ensures that these applications are appropriately evaluated, comply with relevant standards, and provide users with trustworthy and effective tools for managing their health and well-being [124].

7. Open Issues and Future Direction

In the previous section, we thoroughly examined the results. In this part, we look into open concerns and important challenges in-depth.

A. General issues

The application of ML in personal healthcare presents several unique challenges. Supervised learning algorithms rely on the diagnostic labels used to train the system. However, with the heterogeneous nature of mental illnesses, these labels may not be specific enough to produce AI algorithms with high sensitivity and specificity. A possible solution is to employ ML algorithms to expect specific symptoms or outcomes rather than diagnoses. Additionally, the power of DNN can be leveraged to detect new biomarkers for identifying particular illnesses without human supervision. However, a major hindrance to applying ML algorithms is the need to maintain trade secrets, despite the requirement for transparency and reproducibility. Big data are also inherently disorganized and require significant preprocessing before they can be used. Furthermore, the outcomes of ML algorithms must include information about the quality and potential biases of the data used to train the system, a practice which is not currently being followed.

The primary benefit of AI tools is their ability to handle large amounts of data and aid in clinical decision making. Although there are some instances of ML adoption in clinical psychiatry practice and evidence of clinical or economic impact, there are still significant challenges that healthcare systems face in implementing AI models. For example, a study conducted at Yale University implemented AI-based support to develop and select antidepressant therapies. The healthcare system evaluated the implementation's cost–benefit relationship in terms of financial and clinical advantages. However, obstacles such as the high upfront costs of creating specific IT infrastructure, doubts about its effectiveness, and concerns about unintentional consequences persist. Furthermore, allowing more physicians to treat inadequately reimbursed psychiatric illnesses may increase the difficulties for these physicians and decrease their overall productivity, potentially affecting the hospital's income. Both patients and clinicians are also concerned about the eventual adoption of these clinical facilities. Therefore, in order for AI-based clinical facilities to be integrated into hospital-based clinical operations they must be fully integrated into the healthcare culture. AI faces a significant challenge in personal health due to the limited understanding of the principal biological procedures of psychiatric disorders. Therefore, AI systems should be developed independently rather than relying solely on established foundations. However, there is a statistical trade-off when deducing models based on data, where a complex system may overfit and become inconsistent, while a simple model may underfit the data and lose relevant structures. Suitable ML methods must optimize the statistical bias–variance trade-off by determining the best spot for forecasting. While predictive systems assess the accuracy of a created system in predicting future outcomes, descriptive illness systems identify influences on perceivable variables. Despite the trade-off between precision and explainability, explainable systems are necessary to ensure patient safety and build trust in the system. Recent developments in AI include RNN-divergent systems that can handle data inputs in different phases and perform self-assessment to determine which time points and data inputs are most predictive of the result, determine the operational credentials of outcomes, provide visualizing methods, and allow contribution policy mining. In cases where the biological contributions are poorly understood, AI systems may be as transparent as interpretable systems. However, future AI systems should aim to develop transparency in order to support their clinical use. The supervision of AI technologies is essential for reducing bias, especially for frequently evolving AI systems. Ungoverned AI may perpetuate social inequality or indicate biases by producing different results for individuals without any rational basis. Using non-representative or biased training data that mirrors human biases may lead to the emergence of analytic bias in healthcare applications. Training ML models on human preferences may propagate the harmful distribution of inequality.

Also, it is crucial to differentiate between explanatory and pragmatic methods. Pragmatic methods using automated ML help to improve facilities that can lead to robust and accurate predictions with clinical use. Such optimization processes are computationally expensive and are limited by the interpretability of how the different workflows' characteristics are related to the predictions. Explanatory models aim to build connections between variables, providing insight into a system's workings. We require ML facilities that provide pragmatic assistance and are explainable. A more detailed understanding of how to improve AI systems, such as DL, in order to better serve patients is necessary. The term *protected health information* (PHI) is relevant to various data domains, including personally identifiable features such as clinical data, medical history, patient-provided health information, and medical cost claims. Other PHI areas are built by evaluating information that is not directly related to a health condition but which enables health conditions to be inferred. This distinguishes it from consumer-provided health information. A broad range of stakeholders, from healthcare contributors to retailers to IT companies, manage this diverse PHI information.

Efficient management of health information is critical for many reasons, particularly with the increasing digital stockpiles of digitized PHI. However, information interoperability and standardization deficiency present significant obstacles to PHI information sharing and data usage, including AI applications and analytics. Additionally, settings aimed at restricting the leak of personally detectable health information have constrained the stream and enhanced the research expense of accessing PHI information. Furthermore, the ever-increasing popularity of health monitoring applications and tools has led to the development of *patient-generated health data* (PGHD) that are not covered by health support legislation. DL algorithms and the IoB construct a novel classification of predictive personal health information about people and societal behaviors. A wide variety of metadata and probability models can be applied to classify humans, anticipate their behavior, and prioritize healthcare databases relying on these profiles without the consent or awareness of profiled individuals. Ensuring the transparency of personal health data in ML algorithms is another challenge. Despite attempts towards interpretable ML, AI, and explainable AI, transparency is challenging not only for tracking which PHI data are applied but also for contemplating the goals and results of data usage in healthcare.

B. Legal, economic, and social issues

The development of healthcare AI systems in the IoB will inevitably lead to a rise in the popularity of individual healthcare apps and arrangements. Implementing ML in the IoB, say experts in neural networks and AI, would drastically alter healthcare applications. By reducing the potential for human mistakes and relieving the strain that typical clinical activities may put on clinicians, ML has the potential to significantly improve healthcare quality. Clinical standards may necessitate more frequent testing for high-risk patients. Therefore, this may not necessarily lessen the clinician's burden. If ML can be seamlessly incorporated into routine healthcare procedures, it may free up physicians' time for more difficult work and face-to-face interaction with patients. Ophthalmologists can devote more time to patient consultations and operations if they use AI to help them to understand and prioritize fundus photos. Due to AI's potential to replace many healthcare workers in everyday duties, it may restructure the medical profession and modify the personal healthcare reimbursement system. Despite this, there is currently less scientific proof of its effects on clinical staff.

Integration with healthcare AI processes is essential if cutting-edge AI systems are to realize their full potential. However, studies have revealed that there are obstacles to using AI in individual healthcare. Alert weariness, greater physician effort, disruption of interpersonal communication styles, and the emergence of unique dangers that demand a higher degree of diagnostic attention are all recognized as potential unintended outcomes of clinical data systems. For instance, radiologists may miss a detection if a mammography CAD tool returns a false-negative result while interpreting mammography images without CAD. It is challenging to determine the best clinical process that makes the most of AI-assisted detection, even though many CAD models may be tweaked to strike the right balance between specificity and sensitivity for every clinical application. The implementation and design requirements for integrating data systems into healthcare settings are typically determined by healthcare AI providers' and their patients' lack of expertise.

From a legal standpoint, the deployment of healthcare AI systems requires acknowledgment and approval. The FDA must establish premarket approval submissions for AI systems with direct healthcare implications. Policymakers must define specific standards for non-inferiority indication in 510K submissions, such as the quality and credibility of the process and the representativeness and reliability of the data. ML-based models pose a challenge to regulatory agencies as they can quickly evolve with user feedback and data collection. It is unclear how updates should be evaluated, as a new model may perform better overall but worse for certain patient subsets. The FDA has suggested a pre-certification process for AI systems that train and evolve, focusing on the technology developer and the certification of teams responsible for updating and improving AI systems. As healthcare-related data become more common, consent is necessary for data sharing, especially when sensitive data, such as a patient's location, is involved. To address potential legal issues and ensure the use of reliable AI in healthcare, a collaboration between AI investigators, healthcare providers, hospital administrators, and firms is essential to prioritize critical healthcare needs and reduce workflow disruption. Multi-disciplinary cooperation is crucial for the development and deployment of healthcare AI applications.

C. Landscape

AI has significantly improved decision-making and diagnosis in various areas of personal healthcare. However, the impact of this improvement on the overall effectiveness of personal healthcare applications for illness diagnosis and treatment will depend on how well AI applications integrate with a personal healthcare system that is facing significant financial pressures while also adapting to rapid advancements in genomic and molecular science. Healthcare providers will need to adjust to new roles as data interpreters, integrators, and patient advocates, and the healthcare education system must provide them with the appropriate tools and resources to do so effectively. Determining who will be responsible for managing, verifying, or benefiting from the AI application is essential. Balancing market forces and regulatory safeguards to ensure that patients benefit most should be a top priority.

D. Unveiling the Need for Comprehensive Security

AI mimics human intelligence and can perform a wide range of tasks more quickly than humans. However, it cannot make empathetic, impartial, and ethical decisions. Despite AI's potential for super-intelligence, it cannot reflect on itself or differentiate between people, perspectives, values, and morals. Ensuring a secure connection is vital for any IoB system. With the integration of computing, big data, and parallelization, cyber security threats to IoB connections have become more critical. The security of edge layers and IoT devices has been increasingly scrutinized, and research has been conducted on machine-to-machine network protocols and CNN-based techniques to address privacy and security issues. However, reliable device data can still be compromised. ML models have shown promise in dealing with each file as a distinct instance point in such cases. The performance of ML tools in IoB networks has been evaluated in several models and research studies. However, many IoB security concerns lack perspective, having either limited security integration or open-secure vulnerabilities. Addressing IoB security comprehensively is crucial to addressing IoT security issues effectively.

According to Gartner, by 2025, more than half of people will interact with IoB networks managed by private businesses or governments. IoB health apps will be widely used on smartphones, allowing individuals to manage their diabetes through blood glucose and activity tracking. Despite concerns about data privacy, IoB apps and systems using this technology will continue to evolve. The popularity of social media platforms, e-commerce, digital assistants, and other technologies that require personal data suggests that most users will perceive providing behavioral information as acceptable. This allows the IoB to remodel how businesses utilize technology to deal with influencing people. Besides, some other people and technology options apply strong methods to improve IoB systems, such as:

- Developing device monitoring: applying event management, Information sharing, and *intrusion detection systems* (IDSs) can be beneficial. Also, profiling attackers and placing security checks intelligently for ICS and IoB devices by utilizing cybersecurity threat intelligence is possible.
- Enhancing security characteristics: features such as the ability to encrypts all stored and transmitted data could be helpful. In addition, developed authentication protocols can manage communication management.
- Monitoring ICS and IoB policies and guidelines: multiple cybersecurity has been released by the *National Institute of Standards and Technology* (NIST).

E. Securing the IoB

Ensuring the security of IoB systems poses a formidable challenge for various reasons. Notably, time-to-market considerations often take precedence over security as innovators and manufacturers are compelled to generate novel products. Additionally, many businesses remain oblivious to the IT-related vulnerabilities accompanying IoB systems, instead prioritizing the resources, convenience, and automation these systems offer. Interconnected IoB systems can significantly compound the risks posed by distributed infrastructures and national power production. Hence, it behooves enterprises to monitor individual IoB systems and ensure the security of their IoB systems. To this end, robust access control and user authentication measures can be leveraged to restrict IoB system access to only authorized users.

F. The Future Domain of IoB in Medical and Personal Healthcare

In the foreseeable future, tracking mechanisms will be implemented to monitor the performance of purchasing and sales floor personnel. The IoB will play a significant role in enhancing the functionality of the industry. Its objective is to modify decision-making and behavior trends by collecting data from various devices and deducing valuable insights. The IoB is an advanced approach that combines behavioral science and analytics to propel data processing to a new level. The behavioral data collected will be essential in aiding businesses to model and develop techniques, particularly in marketing and sales. It can assess customer data and apply it to promote products more efficiently, ultimately achieving its ultimate objective of selling products. Wearable technology is where the IoB will prove to be particularly beneficial. Companies, sports, and various activities already utilize this technology extensively to collect and share data among a network of online-linked devices. Due to these devices' interconnected nature and ability to perform independent calculations and store data in the cloud, the IoB will become even more complex. Businesses can leverage this technology to implement cutting-edge strategies to marketing products and services and influence the behavior of their staff and customers. The IoB's ability to optimize customer communication based on data gathered will prove useful to businesses.

G. Technical Issues in Advancing AI

Some technological hurdles must still be overcome before AI can revolutionize individual healthcare applications. Care should be made to collect data that are typical of the target patients since ML-based algorithms rely on ready access to large amounts of high-quality training data. For instance, a model trained on the data of a single hospital may fail to generalize to data from other hospitals because of the presence of different types of noise and bias in data from diverse healthcare ecosystems. It has been suggested that agreement detections might improve the performance of the ML models trained on the data, even though the diagnostic job involves an imperfect inter-expert compromise. Managing disparate datasets effectively requires a sufficient amount of information curation. Additionally, getting the gold standard for a patient's clinical condition necessitates professionals to only examine their clinical literature, which is expensive on a societal level. The predictability of these models may be improved using sophisticated algorithms that can control the noise and peculiarities of various datasets. Results from many superior ML models are difficult to comprehend without assistance. Despite this, these models may improve in performance, although it is not simple to transfer intuitive conceptions displaying the outcomes of the models, to discover the model's weakness, or to extract further biological knowledge from these computational "black boxes." Picture classification models may now be visualized by means such as convolutional filters, the relationship between each picture region, or the utilization of saliency maps. For DNN work models trained on data other than pictures, interpreting the model remains significantly more complex; this is a focus of ongoing research efforts. Recent neural network progress has been concentrated on well-defined tasks that do not need the integration of input across several modalities. DNN-based approaches to broad detection and treatment planning are less developed. Despite the success of neural network models and DL in areas such as image classification, sound synthesis, translation, and speech recognition, clinical diagnostic and therapeutic practices often need more context than the limited practices that DL has mastered. Algorithms for the assessment of multi-modality clinical information are also lacking, and it is unclear how to apply transfer learning methods to include insights gained from non-healthcare datasets. This suggests that greater efforts should be made to annotate data and that more data should be collected to enhance end-to-end AI clinical models. It is still difficult to manage a computer environment for collecting, exchanging, and storing electronic health records and other sensitive medical data. Secure data exchange through cloud services is possible with the use of privacy-preserving methods. However, more interpretable apps that match the requirements for clinical data representation are required to enable the wide-scale use of such infrastructure. The integration of information is uneven and delayed across medical applications and geographic areas. However, emerging clinical information application programming interfaces are beginning to reveal differentiated shifts among many HER suppliers, such as reusable and interchangeable healthcare applications. Several AI healthcare applications were described, all of which used previously collected data for inquiry and proof of concept. Clinical research that examines how healthcare AI systems perform in actual healthcare facilities is needed in order to verify their application in the IoB. Trials in theory will be able to better identify the viability of AI models in real-world noisy and varied clinical environments, as well as guide the incorporation of healthcare AI into contemporary clinical procedures.

H. Edge Computing for Personalized Healthcare

A promising future direction to organically combine IoT, existing deep learning model algorithms, and healthcare fields in this matter is the development of edge computing solutions. Edge computing involves processing data closer to the source, such as IoT devices, rather than sending it to centralized cloud servers. We can achieve real-time data analysis and decision-making by implementing edge computing in healthcare applications, enabling timely interventions and personalized healthcare recommendations. In this future direction, IoT devices, such as wearables and sensors, would continuously collect behavioral data from individuals within the Internet of Behaviors. The data would then be processed and pre-processed locally using lightweight deep learning algorithms deployed at the edge nodes. These edge-based models could be trained on vast datasets from cloud-based deep learning models to ensure high accuracy while minimizing computational requirements. By leveraging edge computing, healthcare applications can even operate efficiently in resource-constrained environments, enhance data privacy by reducing the need to transmit sensitive data to external servers, and reduce network latency, leading to faster response times. Moreover, this approach can foster patient empowerment as individuals gain more control over their data and receive immediate feedback on their health-related behaviors. Collaboration among IoT technology experts, deep learning researchers, and healthcare professionals is essential to implement this future direction. Researchers should optimize existing deep learning models for edge deployment, address security and privacy concerns, and develop robust communication protocols between IoT devices and edge nodes. Integrating domain-specific knowledge from the healthcare field will be critical to defining meaningful behavioral patterns and creating personalized health interventions based on edge-processed data. By pursuing this future direction, investigations can shed light on the transformative potential of edge computing in personal health applications that rely on machine learning techniques in the Internet of Behaviors, opening up new avenues for efficient, privacy-preserving, and patient-centric healthcare solutions.

8. Conclusions and Limitations

The field of the IoB is progressing rapidly and is being increasingly applied in various domains, including businesses, healthcare, and industry. However, a crucial question remains: how can the IoB be trained to achieve a high degree of automation? The answer lies in the use of ML methods, which enable computers to perceive and act like humans. This paper focuses on the importance of ML methods for the success of the IoB and its various applications in healthcare, which are categorized based on an ML perspective. We have tried our best to state the consistency and integrity of our paper, to keep the conclusion on the correct track, and to make it as solid as possible. The study conducts an SLR of IoB-based medical and healthcare applications that use ML methods. The review assesses the advantages and drawbacks of various SLR methods and examines the properties often underutilized in these studies, such as accuracy and security. Additionally, the study examines the programming languages used in these methods, with Tensorflow being the most commonly applied language. The study concludes that future ML improvements in the IoB will be based on recently available and well-organized ML methods, leading to a fully autonomous IoB environment with embedded smart abilities. However, despite the potential benefits of the IoB, several challenges still need to be addressed, such as individual businesses, healthcare provision, and technologies. The study also identifies several limitations, including the unavailability of non-English papers and shortcomings in the transparent illustration of applied algorithms. Finally, the study highlights the deficiency of various different available papers published by significant publications.

Nevertheless, some constraints were encountered during our analysis, including the unavailability of non-English papers, which limited our ability to utilize numerous investigation initiatives. Additionally, some of the papers examined had significant limitations in clearly explaining the algorithms used. Finally, another limitation we faced was a shortage of different papers published by significant publications.

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