



Review

Machine Learning Models and Technologies for Evidence-Based Telehealth and Smart Care: A Review

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Abstract: Background: Over the past few years, clinical studies have utilized machine learning in telehealth and smart care for disease management, self-management, and managing health issues like pulmonary diseases, heart failure, diabetes screening, and intraoperative risks. However, a systematic review of machine learning's use in evidence-based telehealth and smart care is lacking, as evidence-based practice aims to eliminate biases and subjective opinions. Methods: The author conducted a mixed methods review to explore machine learning applications in evidence-based telehealth and smart care. A systematic search of the literature was performed during 16 June 2023–27 June 2023 in Google Scholar, PubMed, and the clinical registry platform ClinicalTrials.gov. The author included articles in the review if they were implemented by evidence-based health informatics and concerned with telehealth and smart care technologies. Results: The author identifies 18 key studies (17 clinical trials) from 175 citations found in internet databases and categorizes them using problem-specific groupings, medical/health domains, machine learning models, algorithms, and techniques. Conclusions: Machine learning combined with the application of evidence-based practices in healthcare can enhance telehealth and smart care strategies by improving quality of personalized care, early detection of health-related problems, patient quality of life, patient-physician communication, resource efficiency and cost-effectiveness. However, this requires interdisciplinary expertise and collaboration among stakeholders, including clinicians, informaticians, and policymakers. Therefore, further research using clinical studies, systematic reviews, analyses, and meta-analyses is required to fully exploit the potential of machine learning in this area.

Keywords: machine learning; evidence based; smart care; telehealth; algorithms; artificial intelligence; evidence-based health informatics



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1. Introduction

Machine learning (ML) is a subcategory of artificial intelligence (AI) that enables computers to learn and make decisions without explicit programming. It involves developing algorithms and models that analyze and interpret data, identify patterns, and make informed predictions. It has applications in fields like image recognition, natural language processing, recommendation systems, and predictive analytics. AI, a broad term, encompasses various techniques and approaches, including ML and deep learning.

ML algorithms are divided into several types, each with its own approach and purpose. Supervised learning involves training an algorithm on labeled data, unsupervised learning trains an algorithm on unlabeled data, reinforcement learning involves agents learning through trial and error, semi-supervised learning combines supervised and unsupervised learning, and deep learning uses artificial neural networks to represent complex patterns in data.

Healthcare ML is a powerful tool that can improve patient care and outcomes by aiding in disease diagnosis, analyzing medical images, predicting patient outcomes, optimizing workflows, identifying high-risk patients, and providing personalized medicine. The field is constantly evolving, with new applications being explored to improve patient care, enhance diagnostics, and streamline healthcare processes.

2. Background and Related Work

ML is used to develop models and algorithms for various purposes.

Physicians use data to identify diagnostic patterns and guide treatment. ML algorithms may support clinical experts in this task. However, clinicians must actively participate in implementing these algorithms.

There is a lot of research on ML models and technologies to support telehealth and smart care.

A relative review in the healthcare domain [1] introduces clinicians to the basic concepts of ML, summarizes published data, and presents ways that clinicians can participate in this emerging field.

Another publication [2] reviews current practices, achievements, standards, tools, and translational progress in surgical data science, including different aspects like imaging and robotics, multidimensional data modeling, acquisition and interpretation, and human-machine interfaces for a wide range of medical interventional applications using ML models.

Remote measurement technologies were studied in the review in ref. [3], which found that their combination in linear regression and ML models increased predictive performance.

In another article [4], four conventional classification methods (i.e., SVM (support vector machine), decision trees, random forest, and XGBoost) were evaluated in healthcare, achieving high-quality accuracy. SVMs, RF, and XGBoost outperformed DTs, allowing integration in wearable devices for early eye rubbing detection and keratoconus prevention.

Moreover, artificial intelligence and ML technology have revolutionized drug design and development, addressing challenges like low efficacy, off-target delivery, time consumption, and high cost. These algorithms are applied in various drug discovery processes, including peptide synthesis, virtual screening, toxicity prediction, drug monitoring, and polypharmacology [5].

Another research article [6] presents a classification of ML-based schemes in healthcare, categorized based on data pre-processing methods, learning methods, evaluation methods, and applications. It reviews studies on ML applications in healthcare, aiming to help researchers familiarize themselves with the latest research, recognize challenges and limitations, and identify future research directions.

Also, the article [7] introduces Fuzzy-UCS, a Michigan-style learning fuzzy-classifier system designed for supervised learning tasks. Inspired by UCS, it introduces a linguistic representation of rules to evolve more readable rule sets while maintaining similar performance and generalization capabilities. The system's performance and interpretability are compared with other fuzzy and non-fuzzy learners, demonstrating its competitiveness.

The time windows approach is proposed by Pereira et al. [8] to predict the progression from mild cognitive impairment to dementia, stratifying patients based on clinical information. This method outperforms the First Last approach, allowing early prediction up to 5 years before the event and enabling clinicians to adjust treatments and appointments more effectively.

Imbalanced data is a prevalent issue in classification, particularly in highly imbalanced datasets. Techniques for addressing this problem include undersampling and oversampling at the algorithm and data levels. The article [9] proposes a hybrid method for preprocessing imbalanced datasets using a synthetic minority oversampling technique, rough set theory editing, and the lower approximation of a subset.

Charisma is a new top-down cell segmentation framework for histology images, combining image processing techniques, a supervised trained classifier, and a robust clump splitting algorithm. It outperforms other examined methods in real-world data from intensive care unit patients, demonstrating its effectiveness in understanding disease and treatment responses at the cellular level [10].

The K-nearest neighbors' (KNN) classifier is a popular method for pattern classification, with Fuzzy K-nearest neighbors (FuzzyKNN) being the most notable. A relative work [11] introduces a new approach using interval-valued fuzzy sets, improving its

adaptability to supervised learning problems. By an experimental study compared the IV-KNN classifier to KNN, FuzzyKNN, and other fuzzy classifiers, and found it significantly more accurate.

The early detection of gynecological cancers is crucial for patient outcomes. In the article [12] is studied and found that ML and AI technologies can improve diagnosis accuracy, reduce delays, and potentially eliminate unnecessary operations, requiring collaboration between researchers and data scientists.

In another case a ref. [13] presented AI tools that can help address the quality gaps that are limiting accurate diagnosis and the use of evidence-based interventions to reorient care toward proactive preventative management in chronic obstructive pulmonary disease (COPD).

Also, ref. [14] discusses ML algorithms for atrial fibrillation detection and management and the development of artificial intelligence in cardiology. AI detects AF accurately, but its prediction accuracy is low, necessitating further studies for intervention selection.

Ref. [15] examines the use of Digital Health Technologies (DHTs) in clinical trials registered on ClinicalTrials.gov for chronic neurological disorders, revealing growth in both established and novel digital measures, highlighting key trends and contexts of use.

Ref. [16] found that the use of context-aware computing (CAC) systems in healthcare can be an effective, useful, feasible, and acceptable way to advance medical research and provide health services and is a promising new area of research and development. The evaluation of CAC systems in evidence-based health informatics (EBHI) presents positive effects on the state of health and the management of long-term diseases.

Moreover, the authors of the review in ref. [17] showed that artificial intelligence and ML (AI/ML) in heart failure diagnostics and therapy can improve workflow and outcomes, especially for time series data collected via remote monitoring. However, limitations like data integration, privacy, and challenges in healthcare apply to AI/ML in wearable technology.

Finally, the authors of the survey [18] reviews transformers' applications in medical imaging, identifying challenges, insights, and trends, aiming to spark interest and provide reference. Transformers, which is a deep learning architecture based on the multi-head attention mechanism, have shown success in computer vision, prompting researchers to reconsider convolutional neural networks' superiority.

2.1. Evidence-Based Telehealth and Smart Care

Telehealth (or telemedicine), as defined in MeSH terminology [19], refers to the provision of health services through remote telecommunications. This includes interactive consulting and diagnostic services. Telehealth can include various methods such as video consultations, remote monitoring of vital signs, and the use of mobile apps or messaging platforms for communication between patients and healthcare providers.

Alongside telehealth, smart care (SC) is a health services system that uses technology like wearable devices, IoT, and mobile internet to dynamically access information, and connect people, materials, and institutions that are related to healthcare [20]. It eliminates delays in identifying patient records, improves information exchange among parties, and encourages patient active participation in treatment. SC aims to manage clinical data effectively, ensuring efficient and effective healthcare services.

Moreover, evidence-based healthcare (or evidence-based practice) is a method of healthcare that integrates scientific knowledge with clinical expertise [21]. It involves assessing research data, clinical guidelines, and other resources to identify clinical problems, apply high-quality interventions, and re-evaluate outcomes for improvement. This approach aims to use the best available evidence from scientific research to inform decision-making and improve patient outcomes. It involves integrating clinical expertise, patient preferences, and current research evidence to guide healthcare practices and interventions, ensuring they are based on solid scientific evidence and tailored to individual needs.

Subsequently, EBHI (evidence-based health informatics) is a field that supports health information technology platforms and e-health interventions [22]. It involves the synthesis of optimal evidence from clinical trials for decision-making on HIT introduction and operation [23]. EBHI is crucial for physicians' support in clinical decision-making, relying on accurate data from rigorous studies [24].

EBHI has significantly impacted telehealth and smart care, with a significant increase in physicians recognizing the benefits of digital health tools. An American Medical Association (AMA) study found that the percentage of physicians who believe digital health tools are advantageous for patient care grew from 85% in 2016 to 93% in 2022 [25]. The largest growth in adoption occurred in remote care tools, with tele-visits/virtual visits and remote monitoring devices increasing from 12% in 2016 to 30% in 2021.

A 2021 survey found that 60% of clinicians agreed that telehealth enabled them to provide high-quality care, with 93% conducting live, interactive video visits and 69% engaging in audio-only visits. Telehealth utilization rates were similar across most demographic subgroups but lower among the uninsured and young adults aged 18–24 [26].

More specifically, randomized controlled trials (RCTs) are considered a reliable solution by the health community. A systematic review of RCTs related to health information technology (HIT) and eHealth interventions found that significant improvements were observed in the outcomes of 31 trials out of a total of 51 (60.78%) [27].

This growth highlights the importance of validated and equitable digital health solutions for advancing patient care and streamlining administrative burdens in medicine.

However, while there is much research into ML models and technologies to support telehealth and SC, there is a dearth of research into these models that are additionally evidence based. The study of these models is the focus of this review as the application of this type of them is considered important in the health sector.

2.2. Machine Learning

There are several types of ML algorithms, each with its characteristics and applications. Here are some common types:

- *Supervised Learning (SL) Models*: These models learn from labeled data to make predictions or classifications. SL is a machine learning paradigm where input objects and desired output values are used to train a model [28]. The model maps new data on expected output values, ensuring the algorithm can correctly determine output values for unseen instances. The statistical quality of an algorithm is measured through the generalization error. SL models learn from labeled training data, aiming to find patterns in the data to predict target variables for new, unseen data. Common supervised learning algorithms include linear regression, decision trees, SVMs, neural networks, random forests, logistic regression, and naive bayes.
- *Unsupervised Learning (UL) Models*: Unsupervised learning is the process of grouping data into clusters using automated algorithms to learn underlying relationships or features [29]. Common UL models analyze unlabeled data to discover hidden patterns or structures. Common algorithms include clustering, dimensionality reduction techniques, and association rule learning. Unlike supervised learning, UL learns patterns exclusively from unlabeled data, aiming to build a concise representation of the world through mimicry, generating imaginative content from unlabeled data.
- *Reinforcement Learning (RL) Models*: RL is a model that involves discrete environment states, agent actions, and scalar reinforcement signals. It differs from supervised learning by not presenting input/output pairs and requiring agents to gather experience [30]. It focuses on finding a balance between exploration and exploitation, aiming to maximize long-term rewards, and is closely related to artificial intelligence search and planning issues.
- *Deep Learning (DL) Models*: DL is a rapidly growing machine learning technique that has significantly impacted human life through applications like virtual personal assistants and automated number-plate recognition, but it also faces challenges and

controversies [31]. Deep learning (DL) algorithms are neural networks used to learn hierarchical data representations. They can be supervised, semi-supervised, unsupervised, or reinforcement based. Common DL algorithms include CNN for image analysis, RNN for sequential data analysis, and LSTM for time series data, particularly effective in image and speech recognition.

3. Research Methodology

Blending the above, the combined application of evidence-based telehealth (EBTH) and SC in healthcare systems will be studied below.

3.1. Objectives

This review article explores the use of healthcare ML models and algorithms in EBTH and SC in specific healthcare domains. It also discusses the tasks and evaluation features of these systems, the evaluation metrics used to assess model efficacy, the strengths, weaknesses, and benefits of using these models, and the future directions of these models and technologies in these areas.

3.2. Research Questions

Thus, the author identified seven broad research questions (RQs) that will guide the rest of this work.

RQ1: Which types of Healthcare ML models are used evidence-based telehealth and smart care as these are classified in specific healthcare domains using standard classification systems?

RQ2: What is the classification of studies in the evidence-based telehealth and smart care areas using ML based on health products and services according to their purpose and user perspective?

RQ3: Which ML algorithms and tools are used in evidence-based telehealth and smart care-related problems?

RQ4: What are the most used functional and technical features of ML systems technology to assess the implementation of evidence-based telehealth and smart care?

RQ5: Which evaluation metrics have been used to gauge model efficacy in evidence-based telehealth and smart care?

RQ6: What are the strengths, weaknesses, and benefits of using ML models and technologies for evidence-based telehealth and smart care?

RQ7: What are the future directions of ML models and technologies for evidence-based telehealth and smart care?

4. Materials and Methods

4.1. Search Strategy

A systematic literature search was performed from 16 June 2023 to 27 June 2023 in Google Scholar, PubMed, and the clinical registry platform ClinicalTrials.gov. The author included the articles in the review if they were implemented by evidence-based health informatics and concerned with telehealth and SC technologies.

The following search keywords were used: ((telecare OR ecare OR ehealth OR telemedicine OR telehealth OR mhealth) OR ((Tele monitoring OR Remote monitoring OR Phone OR Mobile) AND (health OR medicine or care))) AND (NCT OR trial OR registration number).

The author also screened the reference lists of relevant articles to ensure that she captured all eligible studies. The implementation of the systematic review followed the PRISMA 2009 flow diagram (Figure 1).

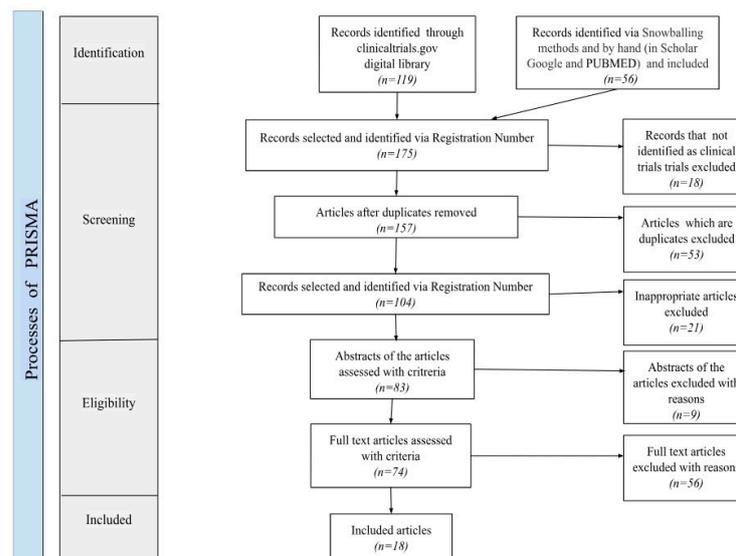


Figure 1. PRISMA 2009 flow diagram of included studies.

4.2. Study Selection Criteria

The author included the studies in the review if these were implemented by evidence-based practices and concerned telehealth and SC technologies.

More analytically, this review includes studies that meet the following criteria:

- focus on users/patients,
- include the use of telehealth and SC as a system, and
- monitor the performance of systems through clinical trials.

In the case of ClinicalTrials.gov, appropriate clinical trials were initially sought using specific keywords. Then, the author searched Google Scholar and PubMed and selected the publications (articles) related to these trials found at ClinicalTrials.gov.

Exclusion criteria: For the final analysis, the author only collected articles containing a trial registration number.

Finally, the author removed articles that were not in English from the final analysis.

4.3. Screening Process

A two-stage review process was performed by the author, (a) initially excluding articles based on the titles and their abstracts, and (b) then excluding the remaining articles by reading the full text of the article.

4.4. Data Extraction and Synthesis Strategy

The author extracted information from the eligible studies into a data mining form, while two external independent evaluators examined the results for consistency and accuracy.

To classify the findings of the review, the following information was collected: author(s), trial registration number, abstract/title/full text, and category of medical/health applications using the ICD-11 classification system [32].

The author grouped the articles into the following categories of medical/health applications using the ICD-11 classification system: Neoplasms—C04, Respiratory Tract Diseases—C08 (Pulmonary Disease—C08.381), Nervous System Diseases—C10 (Multiple Sclerosis C10.114.375.500, Dyskinesias—C10.597.350, Cardiovascular Diseases—C14, Nutritional and Metabolic Diseases—C18 (Glucose Metabolism Disorders—C18.452.394), Pathological Conditions, Signs and Symptoms—C23 (Intraoperative Complications—C23.550.5), and Neurodevelopmental Disorders—F03.625 (Autism Spectrum Disorder F03.625.164.113.500).

The author depicts the analytical results of this process described above in the Section 5 and specifically where the descriptive elements of the studies are described.

From another perspective, the World Health Organization (WHO) has developed the WHO Family of International Classifications (WHO-FIC) and Terminologies classification system based on health domains and interventions to better understand and classify health products and services [33]. WHO-FIC, along with ICD-11, ICF, and ICHI, are global standards for health data, clinical documentation, and statistical aggregation. They facilitate knowledge representation, data transfer, and communication, and are utilized by governments, researchers, doctors, hospitals, laboratories, insurance companies, and international organizations.

Another widely used classification system is the Classification of Digital Health Interventions (DHIs) [34]. More specifically, the DHIs is a framework that categorizes digital and mobile technologies used to support health system needs. It includes functionalities for clients, healthcare providers, health system managers, and data services.

Thus, a synthesis of the WHO-FIC and DHIs classification systems is used to classify the findings of this study by the respective health product or service they support and by the type of ML they use.

A detailed description of this composite classification is provided below:

- The *Health Conditions (HCs)* domain includes diseases, disorders, injuries, and other health problems (e.g., disease diagnosis, clustering, subtyping, and anomaly detection), with the ICD-11 [32] being the classification standard for these health conditions based on their etiology, manifestation, and location [33].
- The *Classification of Digital Health Interventions (DHIs)* categories include targeted client communication (e.g., health behavior modeling), healthcare provider-related functionalities (e.g., clinical decision support, telemedicine), health system management (e.g., healthcare resource allocation), and data services (e.g., predictive analytics) [34].
- The *Interventions on Health Conditions (ICHI)* domain includes preventive, curative, rehabilitative, and palliative (e.g., drug discovery; personalized medicine; genomics and precision medicine) actions to improve or maintain health status. These interventions are classified by the ICHI based on their target, action, means, and provider [33].

Thus, according to the previously mentioned information, the author grouped the articles into the following categories and sub-categories of medical/health applications (products/services that they support):

Category I, as classified by HCs classification system [33]

The following sub-categories of this category were identified in the study:

- Disease diagnosis
- Disease clustering and subtyping
- Anomaly detection

Category II, as classified by DHIs classification system [34]

The following sub-categories of this category were identified in the study:

- Electronic health records
- Telemedicine
- Image analysis
- Patient risk stratification
- Natural language processing
- Clinical decision support
- Healthcare resource allocation
- Health behavior modeling
- Predictive analytics

Category III, as classified by ICHI classification system [33]

The following sub-categories of this category were identified in the study:

- Drug discovery
- Personalized medicine
- Genomics and precision medicine

The author illustrates the analytical results of this process described above in the Section 5 and specifically where the machine learning sectors in evidence-based telehealth and smart care are described.

The mixed methods review guidelines used in the study design are (i) the guidelines for a scope proposed by Arksey and O'Malley [35] and (ii) the Preferred Reporting Items for Systematic Reviews and Meta-Analyses statement [36].

Moreover, the author applied the Delphi method [37] to improve the reliability of the study. Specifically, this study was given to two independent researchers for reading and then all discussed the design and implementation of this study. The author considered the commentators' comments in the final structure of the article.

5. Results

5.1. Retrieved Studies

The database search retrieved 175 citations. The final analysis considered 18 articles that employ 17 clinical studies in total (Table 1) which belong to the following health domains (by the ICD-11 classification system):

Table 1. The studies according to the ICD-11 classification system.

Rank	NCT Number	Articles	Authors	Title
1. C—Diseases				
1.1. Neoplasms—C04				
1	NCT04442425	[38]	(Ordun et al., 2022)	Intelligent Sight and Sound: A Chronic Cancer Pain Dataset
2	NCT04726228	[39,40]	(Cuomo et al., 2023); (Cascella et al., 2021)	Comments on 'Telemedicine for Managing Cancer Pain. A Great Opportunity to be Exploited for CLinical and Research Purposes; Multidimensional Statistical Technique for Interpreting the Spontaneous Breakthrough Cancer Pain Phenomenon. A Secondary Analysis from the IOPS-MS Study
1.2 Respiratory Tract Diseases C08				
1.2.1 Pulmonary Disease C08.381				
3	NCT04240353	[41]	(Taylor et al., 2021)	RECEIVER: Digital Service Model for Chronic Obstructive Pulmonary Disease (COPD)
4	NCT05218525	[42]	(Secher et al., 2022)	Clinical implementation of an algorithm for predicting exacerbations in patients with COPD in telemonitoring: a study protocol for a single-blinded randomized controlled trial
1.2 Nervous System Diseases C10				
1.2.1 Multiple Sclerosis C10.114.375.500				
5	NCT02583386	[43]	(Mosquera-Lopez et al., 2021)	Automated Detection of Real-World Falls: Modeled From People With Multiple Sclerosis
6	NCT03638479	[44]	(Varghese et al., 2019)	A Smart Device System to Identify New Phenotypical Characteristics in Movement Disorders
7	NCT04536701	[45]	(Rose et al., 2021)	Smarthealth technology study protocol to improve relationships between older adults with dementia and family caregivers
8	NCT04939818	[46]	(Hampsey et al., 2022)	Protocol for Rhapsody: a longitudinal observational study examining the feasibility of speech phenotyping for remote assessment of neurodegenerative and psychiatric disorders

Table 1. Cont.

Rank	NCT Number	Articles	Authors	Title
1.2.2 Dyskinesias C10.597.350				
9	NCT04228094	[47]	(López et al., 2023)	APPRAISE-RS: Automated, updated, participatory, and personalized treatment recommender systems based on GRADE methodology
1.3 Cardiovascular Diseases C14				
10	ACTRN12613000715774	[48]	(Redfern et al., 2020)	A digital health intervention for cardiovascular disease management in primary care (CONNECT) randomized controlled trial
11	NCT03474315	[49]	(Michalik et al., 2018)	An interactive assistant for patients with cardiac implantable electronic devices: A study protocol of the LUCY trial
12	NCT04189029	[50]	(Fayol et al., 2022)	Aetiological classification and prognosis in patients with heart failure with preserved ejection fraction
1.4 Nutritional and Metabolic Diseases C18				
1.4.1 Glucose Metabolism Disorders C18.452.394				
13	NCT04204733	[51]	(Ash et al., 2021)	Evaluation of Web-Based and In-Person Methods to Recruit Adults with Type 1 Diabetes for a Mobile Exercise Intervention: Prospective Observational Study
14	NCT04430608	[52]	(Klarskov et al., 2022)	Telemetric Continuous Glucose Monitoring During the COVID-19 Pandemic in Isolated Hospitalized Patients in Denmark: A Randomized Controlled Exploratory Trial
15	NCT05504096	[53]	(Shi et al., 2023)	Assessing Elevated Blood Glucose Levels Using Machine Learning and Wearable Photo plethysmography Sensors
1.5. Pathological Conditions, Signs and Symptoms C23				
1.5.1 Intraoperative Complications C23.550.5				
16	NCT03923699	[54]	(B. Fritz et al., 2022)	Protocol for the perioperative outcome risk assessment with computer learning enhancement (Periop ORACLE) randomized study
2. F- Psychiatry and Psychology				
2.1 Neurodevelopmental Disorders F03.625				
2.1.1 Autism Spectrum Disorder F03.625.164.113.500				
17	NCT03569176	[55]	(Voss et al., 2019)	Effect of Wearable Digital Intervention for Improving Socialization in Children with Autism Spectrum Disorder: A Randomized Clinical Trial

A total of 2 studies/3 articles belong to Neoplasms category, 2 studies/2 articles to Respiratory Tract Diseases, 4 studies/4 articles to Multiple Sclerosis (Nervous System Diseases), 1 study/1 article to Dyskinesias Sclerosis (Nervous System Diseases), 3 studies/3 articles to Cardiovascular Diseases, 3 studies/3 articles to Glucose Metabolism Disorders (Nutritional and Metabolic Diseases), 1 study/1 article to Intraoperative Complications (Pathological Conditions, Signs and Symptoms) and 1 study/1 article belongs to Autism Spectrum Disorder (Neurodevelopmental Disorders).

5.2. Descriptive Elements of the Studies

Regarding RQ1 (Table 1), the author presents a brief description of the studies as classified with the ICD-11 classification system.

When clinical studies fell into more than one health category, the one most strongly supported in the article was selected.

5.2.1. C—Diseases

Neoplasms—C04: The study in ref. [38] aims to create a pain prediction model using natural language processing algorithms, based on facial images, audio signals, self-reported pain, and natural language verbalizations of participant feelings.

Data are combined with self-reported pain and clinical data to create a supervised machine learning model and algorithm (e.g., random forest algorithm) to automatically detect pain.

Another similar trial [39,40] also examines the Cancer Pain and Quality of Life Pain ASsessment in CANcer Patients by Machine LEarning (PASCALe). The PASCALe study evaluates telemedicine's potential to improve cancer patients' quality of life through self-management and remote monitoring. It develops a mobile app to study non-predictable breakthrough cancer pain (NP-BTCP) features, using multiple correspondence analysis (MCA) and hierarchical clustering principal component (HCPC) analysis to identify theoretical clusters.

5.2.2. Respiratory Tract Diseases (C08)

Pulmonary Disease C08.381: The trial in ref. [41] aims to evaluate the adoption of a digital support service model for chronic obstructive pulmonary disease, focusing on ML analysis and predictive modeling, and uses a consented dataset for endpoint analysis and follow-up studies.

Machine learning supported the exploratory analyses of associations and the relative predictive importance of electronic health records, patient-reported outcomes, wearables physiology, and NIV parameters.

Another trial [42] in this domain presents an algorithm testing a prediction algorithm in an operational telehealth system for patients with chronic obstructive pulmonary disease (COPD). A telemedicine system is being evaluated with a COPD prediction algorithm, predicting exacerbations for COPD patients. The main outcome is the number of exacerbations, with secondary outcomes including the cost-effectiveness ratio and quality of life changes. The trial aims to determine if the COPD prediction algorithm can support the early detection of exacerbations in a telehealth setting, potentially reducing hospitalizations.

5.2.3. Nervous System Diseases (C10)

Multiple Sclerosis C10.114.375.500: The study [43] presents a context-aware fall detection system using inertial and time of flight sensors, trained on real-world falls in people with MS. The system achieved a sensitivity of 92.14% and a false-positive rate of 0.65 false alarms per day.

Brain Diseases C10.228.140: The smart device system (SDS) [44] is a technology-based system that uses smartphone questionnaires, smartwatches, and tablet-based Archimedean spirals to measure movement for Parkinson's disease and essential tremor patients, with potential integration with deep brain stimulation, neuroimaging, and biobanks for further analysis.

Also, a modern project [45] aims to develop a monitoring, modeling, and interactive recommendation solution for caregivers in dementia patient care. This study aims to develop a smart health system for monitoring, modeling, and interactive recommendation solutions (for caregivers) for in-home dementia patient care that focuses on caregiver-patient relationships. It uses statistical learning techniques to automate the generation of modules, including classification models, tailored for specific patients, and an adaptive recommendation system to improve familial interactions and reduce caregiver strain.

Moreover, the study in ref. [46] aims to collect speech data remotely from individuals with neurodegenerative and psychiatric disorders using a smartphone app. Participants will complete audio-recorded tasks and symptom scales, measuring executive control and voice quality. The study also evaluates whether acoustic and linguistic patterns can predict diagnostic groups.

Dyskinesias C10.597.350: A recent study [47] aims to assess TDApp2 and compare its recommendations with relevant clinical practice guidelines in children/adolescents with attention deficit hyperactivity disorder. Thus, researchers have developed TDApp, an eHealth tool that provides decentralized, participatory, individualized, and automated pharmacologic treatment recommendations for patients with attention deficit hyperactivity disorder.

This work presents a methodology, which is called APPRAISE-RS (Automated Participatory and Personalized Treatment Recommender System) [47], which uses rule-based systems to recommend automated, updated, participatory, and personalized treatments based on a patient's demographic and clinical data. It gathers information from medical literature, personalizes treatments based on characteristics, and participates in creating a list of treatment outcomes. The system summarizes evidence from all treatments for a patient, ranking them in order of suitability. APPRAISE-RS aims to assist clinicians, not replace clinical judgment.

Cardiovascular Diseases C14: The study in ref. [48] assesses Australian guideline-recommended blood pressure and cholesterol targets, focusing on secondary outcomes like mean blood pressure, fasting cholesterol levels, self-efficacy, health literacy, smoking cessation, body mass index, waist circumference, physical activity, and medication adherence, using a free SMS telemonitoring service with web-based data entry.

Using an algorithm, the telemonitoring system notifies participants when their average blood pressure exceeds the target, reminds them to contact their surgeon, and provides clinicians with readings through a secure web interface.

The study in ref. [49] aims to develop a multivariate model to predict the need for the ambulatory follow-up of implantable cardioverter defibrillators in patients with chronic heart failure. Current devices record patient activity and hemodynamic parameters but increasing numbers of patients with cardiac resynchronization therapy and implantable cardioverter defibrillators devices overload cardiology centers. Remote monitoring can help identify device damage and prevent the exacerbation of chronic heart failure. This study in ref. [49] aims to create an interactive patient's assistant (LUCY), a mobile application, database, and ML system for predicting patient endpoints. It uses data from remote device interrogation and patient health status reports, with a real-time self-learning algorithm for ambulatory visit necessity.

Moreover, a prospective multicenter study [50] aims to understand phenotypic variability in heart failure patients with preserved left ventricular ejection fraction using extensive phenotyping, biomarkers, omics, imaging, and ML-based cluster analysis to identify unique phenogroups.

5.2.4. Nutritional and Metabolic Diseases (C18)

Glucose Metabolism Disorders C18.452.394: The study in ref. [51] aims to create a mobile app for sedentary adults with type 1 diabetes, incorporating biosensor feedback, teleconsultation, and online exercise classes. The app was evaluated for feasibility, acceptability, efficacy, and predictors of physical activity behavior. The results guide context-aware physical activity coaching and related diet and insulin adjustments.

An algorithm was designed that uses identified predictors of physical activity to advise patients on timing and preparation for physical activity.

The study in ref. [52] explores the use of telemetric continuous glucose monitoring in quarantined patients with diabetes and confirmed SARS-CoV-2 infection, aiming to improve glycemic control and reduce patient–healthcare worker contacts, potentially reducing disease transmission and personal protective equipment use and improving clinical outcomes. This model uses the Dexcom G6 sensor which has an upper detection limit, causing collective graphical model trajectories to be properly censored. The complete trajectories were modeled using latent Gaussian processes as an ML technique. The model was implemented in TensorFlow Probability and fitted using a Hamiltonian Markov chain Monte Carlo method.

Another new study [53] utilizes wearable technology, specifically photoplethysmography (PPG) and artificial intelligence, to non-invasively monitor blood glucose levels in diabetes patients, alerting them when unhealthy levels occur.

A risk prediction model is developed using artificial intelligence and ML techniques to identify individuals with unhealthy blood glucose levels based on PPG measurements. Pathological Conditions, Signs and Symptoms (C23)

Intraoperative Complications C23.550.5: The TECTONICS clinical trial [54] aims to evaluate ML's ability to predict postoperative problems in anesthesiology, highlighting the potential of telemedicine in preventing at-risk patient outcomes.

The anesthesia team in the operating room is supported in their work with the integration of machine-learning forecasting algorithms and AlertWatch, which monitors real-time data.

5.2.5. Neurodevelopmental Disorders (F03.625)

Autism Spectrum Disorder F03.625.164.113.500: A clinical trial on Superpower Glass [55], an AI-driven wearable behavioral intervention, showed significant improvements in socialization subscale for children with autism spectrum disorder compared to standard therapy.

The Mobilized ML Autism Risk Assessment (MARA) tool assesses autism severity using a decision tree algorithm, focusing on communication, social reciprocity, and restricted behaviors in parents.

5.3. Classification of Machine Learning Models Based on Their Specific Applications

In the healthcare domain, ML models can be classified into various types based on their specific applications. The following are the most common types of them:

Diagnostic models are tools used to diagnose diseases or conditions by analyzing patient data [44].

Prognostic models predict future outcomes or progression of diseases by estimating the likelihood of certain events [50].

Treatment recommendation models help healthcare professionals make treatment decisions and provide available treatment options [47].

Patient Risk stratification models assess the risk of developing certain diseases or conditions by identifying individuals at higher risk, allowing for targeted interventions and preventive measures [53].

Patient monitoring models continuously monitor patient data to detect deviations from normal patterns and alert healthcare providers to potential issues [38].

Healthcare resource allocation models optimize resource allocation by analyzing patient flow, resource utilization, and demand patterns. These models consider factors like patient characteristics, medical history, and treatment options, enabling informed decisions. They also incorporate guidelines and evidence-based practices to provide personalized treatment plans. By leveraging technology and data-driven approaches, healthcare professionals can optimize resource allocation and improve patient outcomes [41].

5.4. Machine Learning Sectors in Evidence-Based Telehealth and Smart Care

As far as RQ2 is concerned, the findings of this study are described in detail as they are classified a) by the respective health product/service they support and b) by the type of ML they treat (Table 2).

Table 2. The studies sorted according to the health product/service they support and the type of ML they use (symbol explanation: ✓ means this study belongs to this health domain task).

Health Do-Main Task Ref. of the Task	Disease Diagnosis/Management	Disease Clustering and Subtyping	Anomaly Detection	Electronic Health Records	Telemedicine	Image Analysis	Patient Risk Stratification	Natural Language Processing (NLP)	Clinical Decision Support	Healthcare Resource Allocation	Predictive Analytics	Drug Discovery	Personalized Medicine	Genomics and Precision Medicine
	Supervised Machine Learning Approach													
[38]								✓						
[41]				✓							✓			
[42]		✓									✓			
[45]											✓		✓	
[50]	✓	✓									✓			
[52]					✓									
[53]	✓				✓		✓			✓				✓
[54]				✓	✓									
[55]													✓	
Unsupervised Machine Learning Approach														
[39,40]		✓												
Reinforcement Machine Learning Approach														
[51]					✓									
Deep Machine learning Approach														
[44]	✓													
Supervised & Deep Machine learning & Neural Networks														
[49]					✓	✓								✓
Supervised, semi-supervised and Unsupervised Machine Learning Approach														
[43]		✓	✓								✓			
All Approaches														
[46]	✓							✓						
[47]							✓					✓	✓	
Unclear Approach														
[48]	✓	✓			✓				✓					

More specific discussion on these studies follows.

Category I, as classified by HCs classification system, which includes:

- *Disease diagnosis/management healthcare sector:* Approaches identified in this sector mainly belong to two studies on the supervised machine learning approach [50,53], one study on the deep learning approach [44], one study [46] on all approaches, and one more study [48] that uses statistical analysis, the backbone of ML, but does not describe

an ML approach clearly. Basically, this sector uses algorithms that can be trained on labeled medical data to classify and diagnose diseases based on symptoms, medical images, or patient data. These algorithms are being used in various fields, including cancer diagnosis, cardiovascular disease diagnosis, diabetes diagnosis, respiratory disease diagnosis, and neurological disease diagnosis. The study in ref. [44] uses logistic regression analysis to compare the performance of deep learning black boxes with classical statistical approaches. It uses univariate and multivariate analyses, including logistic regression, to understand the relationship between input features and classification results. This helps in comparing the performance of these models with classical statistical approaches.

- *Disease clustering and subtyping healthcare sector:* Approaches identified in this sector belong to two studies on the supervised machine learning approach [42,50]; one study (as described in two articles) on the unsupervised approach [39,40]; one jointly examining supervised, semi-supervised, and unsupervised machine learning approaches [43]; and one more with an unclear approach [48]. Disease clustering and subtyping is a method of identifying patterns or groups within a disease population based on specific characteristics, such as clinical features or genetic markers. This helps researchers understand the disease's heterogeneity and potentially identify different disease mechanisms or treatment approaches for each subtype, thereby improving their understanding of the disease [43]. Disease clustering involves using unsupervised and etiology-independent clustering analysis to identify patient groups with similar characteristics or disease patterns. This method uses machine learning techniques to classify patients into distinct phenogroups based on clinical characteristics and treatment responses [50]. More specific ML has been applied to disease subtyping in various types of diseases. Some examples include multiple sclerosis (MS) [43], and chronic obstructive pulmonary disease (COPD) [42].
- *Anomaly detection healthcare sector:* One study [43] is identified in this health sector that mainly belongs to the supervised machine learning approach.
- The development of anomaly detection algorithms in health and medicine is crucial for identifying deviations from normal patterns, aiding in the early diagnosis of health conditions. More specifically, it helps in identifying outliers in physiological signals, abnormal heart rate variability, and unusual patterns in patient data, such as changes in speech or language [56].

Category II, as classified by DHIs classification system, which includes:

- *Electronic health records (EHR) healthcare sector:* Approaches [41,54] identified in this health sector mainly belong to the supervised machine learning approach. The supervised learning approach in the EHR sector uses algorithms that can analyze large volumes of patient data from electronic health records including medical history, lab results, medications, and demographics. The results can help identify high-risk patients, predict patients' results, support clinical decisions, monitor diseases, and more generally support in the health management of the population and the improvement of the supply of health care.
- *Telemedicine healthcare sector:* Approaches identified in this sector belong to the supervised machine learning approach [52–54], to the reinforcement machine learning approach [51], to the supervised and deep machine learning and neural networks approaches [49], and to an unclear approach [48]. More specifically, supervised learning algorithms can be employed in telemedicine applications to analyze patient data collected remotely and provide diagnostic recommendations or monitor disease progression [52–54]. Moreover, the deep learning approach can analyze data from wearable devices, detect anomalies, and provide personalized health recommendations. This approach enables remote monitoring and the early detection of health issues [49].
- *Image analysis healthcare sector:* One study [49] is identified in this sector that belongs to the supervised, deep machine learning and neural networks approaches. This study aims to implement machine learning and artificial intelligence in optimizing

healthcare for patients with cardiac implantable electronic devices. This study is an open product, available for additional testing and improvement with supplementary functionalities: quality of life assessment, teleconsultation, video-streaming, and automated image recognition.

- *Patient risk stratification healthcare sector:* In this sector, two studies [47,53] are identified, the first dealing with all types of machine learning and the second with the supervised machine learning approach. In these studies, algorithms are used to analyze personal data, identify patterns, and group patients based on their profiles. This approach enables the use of personalized medicine, helps healthcare providers prioritize interventions, and allocates resources effectively. More specifically, in the second study [53] various machine learning algorithms were applied for risk stratification, with the SVM model showing the best prediction performance at 84.7%.
- *Natural language processing (NLP) healthcare sector:* The studies identified in this healthcare sector mainly belong to all types of machine learning methods [46] with an emphasis on the supervised learning approach [38]. NLP can be used for various tasks such as text classification, sentiment analysis, named entity recognition, machine translation, text generation, and question answering. These techniques classify text, analyze sentiment, extract named entities, and develop translation models. They can also generate human-like text and answer questions based on a given text or knowledge base [46]. Also, a random forest machine learning algorithm, as a supervised ML approach, that combines multiple decision trees to make predictions was used in three experiments in the study by ref. [38] to show the accuracy of pain scores in chronic cancer patients.
- *Clinical decision support healthcare sector:* One study [48] is identified in this sector, but it is unclear what machine learning approach it supports. Clinical decision support can provide decision support to healthcare professionals by analyzing patient data and recommending appropriate treatment options.
- *Healthcare resource allocation healthcare sector:* One study [53] is clearly identified as managing issues related to the management of limited resources, alongside managing medical issues. Resource allocation is the process of allocating available resources to various uses, particularly in health care. However, at-risk individuals often find it difficult to comply due to the cost of diagnostic tests and scarce medical resources. Resource constraints can affect health care by reducing access to care, compromising quality of care, and limiting treatment options, thus leading to worse health outcomes, and exacerbating existing health disparities. Resource allocation is critical to optimizing productivity, managing costs, and ensuring the strategic use of resources. Thus, beyond the medical issues they cover, many applications in the health field aim to solve the issue of limited resources. For example, BGEM™ is a cloud-based solution that uses advanced machine learning functions to monitor multiple digital biomarkers and provide targeted information to high-risk individuals who would otherwise not have access to the prevention and early treatment of their health problems.
- *Predictive analytics healthcare sector:* Approaches identified in this health sector mainly belong to the supervised machine learning approach [41–43,45,50]. Supervised ML approaches are widely utilized for predictive analytics in healthcare, including predictive analytics for classification, regression, clustering, time series analysis, and recommendation systems [47]. Ref. [41] studies predictive management in healthcare. ML analysis and modeling based on available data have shown promise in predicting outcomes (such as admission and length of stay) for severe COPD exacerbation. These models utilize EHR at triage assessment to make predictions. Also, the authors of ref. [43] studied supervised, semi-supervised, and unsupervised ML techniques in a multimodal machine-learning-based system for anomaly and fall detection, combining heuristics and hard rules based on acceleration magnitude features.

Category III, as classified by ICHI classification system, which includes:

- *Drug discovery healthcare sector*: In this sector, one study [47] is identified which deals with all machine learning approaches. The development of this sector can help identify patterns and relationships in large datasets of chemical compounds, aiding in the discovery of new drugs and understanding their mechanisms of action. Supervised learning, reinforcement learning, and deep learning are algorithms used in drug discovery to predict the effectiveness and safety of new compounds. Supervised learning predicts drug efficacy based on molecular structures and biological data, reinforcement learning optimizes candidate selection and design, and deep learning analyzes large datasets to identify potential candidates.
- *Personalized medicine healthcare sector*: Approaches identified in this health sector mainly belong to the supervised machine learning approach [45,55]. Moreover, one study belongs to supervised, deep machine learning, and neural networks [49], and one more study [47] studies all approaches. Personalized medicine is used to develop personalized care plans based on individual patient characteristics, optimizing treatment effectiveness, and minimizing side effects. Decision trees are often used for specific cases including personalized medicine and treatment recommendations are made based on historical data to guide treatment decisions, benefit–risk judgment, and quality analysis. These tools help weigh different treatments and predict the optimal medication for individual patients, ultimately improving overall patient outcomes [47].
- *Genomics and precision medicine healthcare sector*: In this sector, one study is identified that belongs to the supervised machine learning approach [53].

5.5. Machine Learning Algorithms in Evidence-Based Telehealth and Smart Care

In this study, several algorithms were identified in their respective contexts. The following is a short description of the algorithms mentioned in EBTC and SC:

1. Supervised machine learning algorithms:

- *A linear classifier*: This is a type of machine learning algorithm that separates data points into different classes using a linear decision boundary. Linear classifiers are used in various cases [43,53] in EBTM and SC. These studies demonstrate the use of linear SVM classifiers in different contexts, such as fall detection and blood glucose level detection. A linear classifier classifies data based on a linear combination of input features. In terms of classification, linear classifiers can be classified into two main types: binary linear classifiers and multi-class linear classifiers. Binary linear classifiers are used for binary classification tasks, where the goal is to separate data points into two classes. A binary linear classifier is a machine learning model used for binary classification tasks, dividing instances into two classes based on features. It assigns a class label to each instance based on its position on the linear boundary and makes predictions by calculating a weighted sum of feature values [43]. Examples of binary linear classifiers include logistic regression and SVM with linear kernels [53]. Multi-class linear classifiers are used for multi-class classification tasks, where the goal is to separate data points into more than two classes. An example of a multi-class linear classifier is the SVM with a linear kernel. Mosquera-Lopez et al. [43] discuss the use of support vector machine (SVM) models (the linear SVM classifier and SVM model with a radial basis function kernel) for fall detection. Specifically, the linear SVM classifier separates classes by finding a hyperplane that maximally separates the data points of different classes in the feature space. It assigns new instances to classes based on which side of the hyperplane they fall on. This type of classifier is commonly used in tasks such as image classification, text categorization, and sentiment analysis [43]. Indeed, according to [53], the SVM can be used as both a binary linear classifier and a multi-class linear classifier. Overall, linear classifiers are effective for linearly separable data and can provide good performance in many classification tasks.

- *KNN*: KNN is an ML algorithm commonly used for classification and regression tasks in EBTC and SC [44,50,51].
2. Reinforcement machine learning algorithms.
 - *Contextual bandit algorithm*: This algorithm is used in an in-home monitoring system to make recommendations based on the caregiver's interaction history, current behaviors, and other observations. It helps increase the utility of the system's recommendations and the acceptance of those recommendations by the end users [45].
 3. Support of many types of machine learning algorithms.
 - *Machine learning fall detection algorithms*: These algorithms use ML techniques to detect falls. The accuracy of the detector is improved by training the algorithm using real-world fall data from the target population [43]. This algorithm combines an auto-encoder, which is an unsupervised learning algorithm, and a hyper-ensemble of balanced random forests to detect fall candidates based on acceleration data. The auto-encoder re-constructs the input acceleration signal, identifying fall candidates with a root-mean-square error (RMSE) higher than a certain threshold. The hyper-ensemble of balanced random forests assigns final labels to fall candidates, reducing false positives. This two-stage classification method aims to improve fall detection accuracy in real-world scenarios by combining acceleration and movement features. By combining both acceleration and movement features, this algorithm aims to improve the accuracy of fall detection in real-world scenarios [43].
 - *APPRAISE-RS*: This algorithm is used to develop recommender systems that provide automated, updated, participatory, and personalized treatments. It uses rule-based systems that belong to the symbolic or knowledge-based learning approach and the GRADE heuristic to form recommendations [47]. Specifically, rule-based systems, categorized as supervised, unsupervised, or reinforcement learning, use rules to make decisions or solve problems. They can also be integrated with deep learning models for enhanced performance.
 - *Real-time self-learning algorithm*: This is an algorithm that can continuously learn from and adapt to new data in real time. Real-time self-learning algorithms can be implemented using various methods, such as neural networks, deep reinforcement learning for autonomous driving simulations, and unsupervised learning for real-time learning from unlabeled data. The study by ref. [49] is designed to update its knowledge and improve its performance as it receives new information. This type of algorithm is often used in applications where the data are dynamic and constantly changing, such as in online recommendation systems, fraud detection, or autonomous vehicles. The algorithm uses techniques such as online learning or incremental learning to update its model and make predictions or decisions. This algorithm is used in the health care optimization of patients with cardiac implantable electronic devices (CIED).

5.6. Machine Learning Tasks used in Evidence-Based Telehealth and Smart Care

Regarding RQ3, in EBTH and SC-related problems, several ML tasks can be used to classify, analyze, and interpret data. These tasks include:

Predictive modeling: This is a powerful tool in machine learning that allows for the development of models that can make predictions based on historical data [53]. ML algorithms are used to predict various outcomes in telehealth, such as predicting exacerbations in patients with COPD based on physiological parameters [41,42].

Classification: ML algorithms can classify patients into different risk categories based on their health data [50]. For example, patients can be classified into high-risk or low-risk groups for developing certain conditions or experiencing exacerbations.

Feature selection: ML algorithms are used to identify suitable features or variables for the prediction of exacerbations [53]. This helps in identifying the key factors that should be monitored and considered in telehealth interventions.

Clustering: ML algorithms are used to group patients with similar characteristics or patterns of symptoms [50]. This can help in personalizing telehealth interventions and tailoring them to the specific needs of different patient clusters.

Anomaly detection: This is a technique used to identify patterns or instances that deviate significantly from the normal behavior of a dataset [43]. ML algorithms may detect anomalies or deviations from expected patterns in patient's physiological parameters.

Regression: Used to predict numerical values or continuous variables, such as predicting the progression of a disease or estimating patient outcomes [55]. For example, predicting the length of hospital stay or the risk of readmission for a patient.

Natural language processing (NLP): This is a field of artificial intelligence that analyzes and extracts information from unstructured text data, such as medical records, clinical notes, or patient feedback [38,46]. It focuses on the interaction between computers and human language. It involves the development of algorithms and models that enable computers to understand patient symptoms, disease progression, treatment plans, treatment effectiveness, and outcomes or adverse events. These algorithms and models can also interpret and generate human language in a way that is meaningful and useful.

Time series analysis: This method involves analyzing data collected to find trends and anomalies. This can be useful in monitoring patient vital signs, disease progression, or treatment effectiveness [41,53,54].

Recommendation systems: This method involves providing personalized recommendations for treatment plans, interventions, or healthcare services based on patient data and historical records. This can help in improving patient outcomes and adherence to treatment plans [45,47].

These ML tasks can be combined and customized to address specific challenges in EBTH and SC, enabling healthcare providers to make data-driven decisions, to improve the effectiveness of telehealth interventions by providing timely alerts, personalized care, and better management strategies.

5.7. Functional and Technical Features of ML Systems Technology Applied to Evidence-Based Telehealth and Smart Care

As far as RQ4 is concerned, an ML system can be used in healthcare to address various health-related problems by leveraging ML algorithms to provide solutions. The following are some commonly used functional and technical features of ML systems technology that are applied to telehealth and evidence-based smart care:

Understanding and analyzing medical data: The ML system can process and analyze large volumes of medical data, including text, audio, and video, to extract valuable insights and patterns [44].

Patient engagement: The ML system can engage with patients, providing them with personalized information, answering their queries, and offering guidance on healthcare topics [41,51].

Fact-checking and information verification: An ML system can ensure access to reliable and up-to-date information through the development of ML algorithms for real-time decision-support instruments. These algorithms are designed to dynamically assess risk, diagnose negative patient trajectories, implement evidence-based practices, and improve outcomes for patients. By leveraging these technologies, the ML system aims to provide evidence-based care and improve the quality-of-care metrics [54].

Integration with databases and patient care directives: The ML system can integrate with databases and patient care directives, allowing healthcare teams to access the most up-to-date information and guidelines [47,48].

Global (multilingual or different accents and dialects) interaction: The ML system can interact with users in multiple languages, enabling clear communication and addressing the needs of a global user base [46].

Customization for specific healthcare challenges: The ML system can be tailored to address the nuanced challenges and questions specific to the healthcare industry, providing customized solutions [51].

These features of the ML system help healthcare organizations improve patient care, enhance operational efficiency, and ensure accurate and reliable information dissemination.

5.8. Evaluation Metrics in Evidence-Based Telecare and Smart Care

Regarding RQ5, the evaluation metrics used in EBTC and SC can vary depending on the specific study or trial. However, some common evaluation metrics include:

Health and clinical outcomes: This metric evaluates the impact of EBTC and SC on patient clinical and health outcomes, such as physiological parameters relevant to the specific condition, improvements in chronic disease management, reduction in hospital readmissions, or overall health status and quality of life [41]. These can be measured using questionnaires such as the 12-Item Short Form Health Survey (SF-12) or the EuroQol 5-Dimension (EQ-5D) questionnaire [41,42,48]. These questionnaires assess various aspects of a patient's physical and mental well-being.

Cost-effectiveness: This metric evaluates the economic impact of EBTC or SC interventions by comparing the costs associated with the intervention to the outcomes achieved [42,51].

Treatment adherence: This can be assessed through measures of medication adherence or adherence to recommended lifestyle changes [47,48,55].

Access to care: This metric assesses how EBTC and SC services improve access to healthcare, especially for people living in rural or underserved areas [38,41].

Provider efficiency: This metric evaluates the efficiency and productivity of healthcare providers using EBTC and SC technologies. It can include factors such as reduced appointment wait times, increased patient throughput, or improved documentation and communication [41].

Technology adoption: This metric assesses the adoption and utilization of EBTC and SC technologies by both patients and healthcare providers. It can include factors such as usage rates, user experience, and satisfaction, or training needs [41,48].

The specific evaluation metrics used may vary depending on the study or trial design, the target population, and the specific goals of the specific EBTC or SC intervention.

6. Discussion

The contribution of this review article is to study and analyze ML models and technologies that support telehealth and smart care in the health sector. It focuses on evidence-based models and their application in various health domains and tasks. The article provides detailed findings and classifications of studies based on the health domain, product/service they support, and the type of ML they use.

Specifically, ML models and technologies can be applied in telehealth and SC in various ways. These include risk prediction, remote monitoring, personalized treatment plans, decision support systems, telemedicine triage, patient demographics, clinical measurements, EHRs, remote patient monitoring, and NLP.

Summarizing the investigation for RQ1, as it is stated that in this review, 17 relevant clinical trials concerning the development of pain prediction models, telemedicine services, and telehealth systems for various diseases were identified. In detail, two trials were identified in the health domain of neoplasms, two trials in the health domain of respiratory tract diseases, five trials in nervous system diseases, three trials in cardiovascular diseases, three trials in nutritional and metabolic diseases, one trial in pathological conditions, signs, and symptoms and one more trial was identified in autism spectrum disorder.

In relation to the RQ2, the answers given are summarized as follows:

In the Health Conditions category based on the ICD-11 Standard, four healthcare sectors were identified: disease diagnosis (five trials), clustering and subtyping (five trials in six studies), and anomaly detection (one trial).

In the Classification of Digital Health Interventions category based on the DHIS Standard the following sectors were identified: electronic health records (EHR) (two trials), telemedicine (six trials), image analysis (one trial), patient risk stratification (two trials), natural language processing (NLP) (two trials), clinical decision support (one trial), healthcare resource allocation (one trial), and predictive analytics (one trial).

In the ICHI category, the following sectors were identified: interventions into drug discovery (one trial), personalized medicine (four trials), and genomics and precision medicine (one trial), using machine learning for drug efficacy, safety, and optimal treatment.

Regarding RQ3, the given answers indicate that ML tasks are utilized to classify, analyze, and interpret data in EBTH and SC-related problems. These tasks include predictive modeling, classification, feature selection, clustering, anomaly detection, regression, NLP, time series analysis, and recommendation systems [45,47]. These tasks help predict outcomes, categorize patients, identify suitable features, detect anomalies, and improve treatment outcomes and adherence to treatment plans.

Regarding RQ4, an ML system can be used in healthcare to address health-related problems by analyzing large volumes of medical data. It can provide valuable insights, engage patients, verify medical information, integrate with databases and patient care directives, enable global interaction in multiple languages, and customize solutions for specific healthcare challenges. These features help healthcare organizations improve patient care, enhance operational efficiency, and ensure accurate and reliable information dissemination.

Also, regarding RQ5, the evaluation metrics used in EBTC and SC can vary depending on the study or trial. Common metrics include health and clinical outcomes, cost-effectiveness, treatment adherence, access to care, provider efficiency, and technology adoption. Health and clinical outcomes measure the impact of EBTC and SC on patient health, while cost-effectiveness compares the economic impact of interventions. Treatment adherence measures the adherence to medication or lifestyle changes. Access to care evaluates the improvement in healthcare access, while provider efficiency measures the efficiency and productivity of healthcare providers.

As far as RQ6 is concerned, ML models and technologies offer several advantages in EBTH and SC. They can provide personalized care based on individual patient characteristics. This can improve outcomes by tailoring interventions to each patient's specific needs. ML can also optimize healthcare resources, leading to more efficient care delivery and reduced costs. It can enable the continuous monitoring of patients remotely, providing real-time data collection and analysis. Additionally, ML models can improve patient engagement by providing personalized feedback, reminders, and educational resources. These capabilities can enhance the effectiveness of telehealth and SC by improving prediction, personalization, efficiency, continuous monitoring, and patient engagement.

ML models and technologies for EBTH and SC face several weaknesses. These include limited data, a lack of interpretability, generalizability, ethical considerations, and integration challenges. Limited data may be available for specific patient populations or rare conditions. Models trained on one dataset may not generalize well to other populations or healthcare settings, limiting their applicability in real-world scenarios. Ethical concerns, such as the privacy and security of patient data, potential biases in algorithms, and the impact on doctor-patient relationships, need to be addressed in EBTH and SC. Integration challenges, such as seamless integration with electronic health records and other healthcare technologies, may also pose challenges.

The benefits of EBTH and SC models, as highlighted in this article, include the following:

The early detection of exacerbations: ML algorithms can analyze physical measurements and other patients' characteristics to predict and detect exacerbations earlier [42]. This allows for timely intervention and preventive treatment, leading to faster recovery and a decreased risk of emergency hospitalization.

Personalized care: By utilizing ML, telehealth interventions can be tailored to individual patients based on their specific needs and risk factors [48,51]. This enables more targeted and effective management strategies, improving outcomes and optimizing the use of healthcare resources.

Improved patient–clinician communication: Digitizing routine clinical care and implementing patient–clinician messaging systems can enhance communication and data exchange between patients and healthcare providers. This streamlines the process, reduces inefficiencies, and enables remote management and support for COPD self-management [41].

Enhanced care quality: ML models can analyze data generated by remote monitoring systems, allowing for data mining and advanced data analysis techniques [45]. This can lead to improved health measurement algorithms and the assessment of required ambulatory follow-up, enhancing the quality of care provided to patients [49].

Cost-effectiveness: By identifying high-risk patients and implementing targeted interventions, ML models can help optimize the allocation of healthcare resources. ML algorithms can help identify the subgroup of patients with severe health conditions, e.g., COPD who are most likely to benefit from telehealth interventions [41]. This can lead to cost savings by focusing resources on those who will benefit the most and reducing hospital admissions, emergency visits, and unnecessary treatments [42,51].

Improved resource efficiency: ML can help optimize the use of scarce healthcare resources by identifying patients at risk of exacerbations [41,42]. This allows for targeted interventions and the efficient allocation of resources.

Enhanced quality of life: Telehealth interventions supported by ML have shown promising results in terms of improved health-related quality of life, and increased sense of control, freedom, and security for patients [42,52].

In addition, a weakness of this research article is that it does not benchmark the methods and technologies applied in EBTC and SC.

The choice of method or technology would depend on the specific healthcare challenge and the desired outcome. Moreover, to have a thorough and reliable benchmarking of methods and technologies applied in the field of telehealth and smart care in evidence-based practice, a systematic review and meta-analysis should be performed. A meta-analysis can provide a more accurate and precise estimate of the effect of an intervention or the relationship between similar variables of one or more studies. Specifically, a meta-analysis involves comparing relevant data to find the best solution for a research question. For instance, examining the clinical effectiveness of telehealth for chronic diseases requires examining the type and duration of intervention, primary and secondary clinical outcomes, effect size, and potential moderators.

However, this research article is a mixed-methods review, so by its nature, it cannot precisely answer such specific questions. The chosen studies in this review address research questions but lack a comparative evaluation of methods and technologies, limiting their ability to address these issues (e.g., heterogeneity in the type of measurements and sample characteristics, ML telehealth and smart care models and technologies can be applied in various ways and many different health care domains, services, products, etc.).

Overall, this review ascertained that ML models and technologies in EBTH and SC enable early detection, personalized care, efficient resource allocation, and improved quality of life for patients.

While ML shows promise in EBTH and SC, further research and evidence are needed to fully realize its potential and improve the outcomes of these interventions. Therefore innovations that empower self-management, facilitate integrated clinical care and support delivery of evidence-based treatment interventions are urgently required [41].

7. Future Directions and Challenges

Regarding RQ7, the future directions of ML models and technologies for EBTH and SC include the following:

Improved prediction algorithms: ML algorithms can be further developed to enhance their accuracy in early disease prediction and diagnosis. This can help healthcare providers intervene earlier and provide preventative treatment [42,46,53].

Personalized care: ML models can be used to identify individual patients at immediate health risk and tailor telehealth interventions to their specific needs. This can improve the efficiency and results of telehealth solutions [47,48].

Integration of multiple data sources: ML models can be trained on a wide range of data sources, including patient-generated data, electronic health records, and wearable devices. This integration of data can provide a more comprehensive view of a patient's health and enable more accurate predictions and personalized care [38,49].

Real-time monitoring and feedback: ML models can be used to continuously monitor patients' vital signs and symptoms in real-time. This can enable early interventions and provide feedback to patients, enabling them to better manage their condition [49].

Enhanced decision support: ML models can assist healthcare providers in making evidence-based decisions and providing recommendations for treatment plans and interventions [47].

Overall, the future of ML in telehealth and SC holds great potential for improving patient outcomes, enhancing personalized care, and optimizing healthcare resource utilization.

8. Conclusions

ML models and technologies in EBTH and SC have the potential to improve healthcare outcomes by enabling early detection [42,46], personalized care [47,48], improved resource efficiency [41], and improved quality of life for patients [40–42,47–49].

ML models can be applied in various ways in telehealth and SC, including prediction [53], remote monitoring [39,40,49], personalized treatment plans [44,49], decision support systems [47], telemedicine triage [52–54], patient demographics [41,46,47,54,55], clinical measurements [41,42,48,51,52], EHRs [41,48,54], and NLP [38,46].

As also described in the Section 5, the research identified relevant clinical trials examining EBTH and SC in various health domains, including neoplasms, respiratory tract diseases, nervous system diseases (such as multiple sclerosis), cardiovascular diseases, glucose metabolism disorders, pathological conditions, signs and symptoms, and neurodevelopmental disorders (such as autism spectrum disorder).

It was also revealed that ML tasks utilized in EBTH and SC include predictive modeling, classification, feature selection, clustering, anomaly detection, regression, NLP [38,46], time series analysis [41,53,54], and recommendation systems [45,47]. These tasks help predict outcomes, categorize patients, identify suitable features, detect anomalies, and improve treatment outcomes and adherence to treatment plans.

In addition, it appeared that deep learning approaches [44] are rapidly evolving in healthcare and are being used to analyze and interpret complex medical data in various health domains. New use cases are constantly being explored, and deep learning algorithms are applied in various fields such as the NLP healthcare sector, disease diagnosis and management, telemedicine, genomics and precision medicine and medical imaging [56,57].

ML systems can address health-related problems by analyzing large volumes of medical data, providing valuable insights, engaging patients, verifying medical information, integrating with databases and patient care directives, enabling global interaction in multiple languages, and customizing solutions for specific healthcare challenges.

ML models and technologies in EBTH and SC have the potential to enhance patient-clinician and within-clinicians communications, improve care quality, optimize the allocation of healthcare resources, improve health measurement, provide ambulatory follow-up assessments, improve resource efficiency, and enhance the quality of life for patients while remaining cost-effective.

However, they face challenges like limited data and ethical considerations.

Moreover, the development of these models and technologies involves interdisciplinary expertise in the fields of medicine, nursing, psychology, and computer science engineering.

Thus, further research using systematic analysis and meta-analysis is needed to evaluate the methods and technologies used in EBTH and SC and to fully realize the potential of machine learning in this domain and improve the outcomes of these interventions.

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Abbreviations

12-Item Short Form Health Survey	SF-12
Artificial intelligence	AI
Cardiac implantable electronic devices	CIED
Chronic obstructive pulmonary disease	COPD
Classification of Digital Health Interventions	DHIs
Context-aware computing	CAC
Convolutional neural networks	CNN
Deep learning	DL
Deep q-networks	DQNs
Digital health technology	DHT
Electronic health records	EHR
Evidence-based telehealth	EBTH
EuroQol-5 Dimension	EQ-5D
Fuzzy K-nearest neighbors	FuzzyKNN
Hierarchical clustering principal components	HCPC
International Classification of Diseases 11th Revision	ICD-11
K-nearest neighbor	KNN
Long short-term memory	LSTM
Multiple correspondence analysis	MCA
Mobilized ML Autism Risk Assessment	MARA
Multiple sclerosis	MS
Natural language processing	NLP
Non-predictable breakthrough cancer pain	NP-BTcP
Point-of-care	POC
Principal component analysis	PCA
Machine learning	ML
Photoplethysmography	PPG
Research question	RQ
Smart care	SC
Supervised learning	SL
Reinforcement deep learning	RDL
Reinforcement learning	RL
Recurrent neural networks	RNN
Support vector machine	SVM
Type 2 diabetes mellitus	T2DM
Unsupervised learning	UL

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