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Towards Integration of Artificial Intelligence into Medical Devices as a Real-Time Recommender System for Personalised Healthcare: State-of-the-Art and Future Prospects

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Abstract

In the era of big data, artificial intelligence (AI) algorithms have the potential to revolutionize healthcare by improving patient outcomes and reducing healthcare costs. AI algorithms have frequently been used in health care for predictive modelling, image analysis and drug discovery. Moreover, as a recommender system, these algorithms have shown promising impacts on personalized healthcare provision. A recommender system learns the behaviour of the user and predicts their current preferences (recommends) based on their previous preferences. Implementing AI as a recommender system improves this prediction accuracy and solves cold start and data sparsity problems. However, most of the methods and algorithms are tested in a simulated setting which cannot recapitulate the influencing factors of the real world. This review article systematically reviews prevailing methodologies in recommender systems and discusses the AI algorithms as recommender systems specifically in the field of healthcare. It also provides discussion around the most cutting-edge academic and practical contributions present in the literature, identifies performance evaluation matrices, challenges in the implementation of AI as a recommender system, and acceptance of AI-based recommender systems by clinicians. The findings of this article direct researchers and professionals to comprehend currently developed recommender systems and the future of medical devices integrated with real-time recommender systems for personalized healthcare.

Keywords: *Artificial intelligence, recommender systems, personalized healthcare, performance validation.*

1 Introduction

In recent years, recommender systems (RS) have attracted the interest of researchers from various fields [1]. Recommender systems solve the information overload problem and aim to predict if a certain factor would be beneficial to a user based on certain pre-existing information [2]. In the field of the medical care system, important decisions are to be made urgently and at critical moments based on multiple factors. Artificial intelligence (AI) can greatly enhance personalized service to patients in need. AI has been widely used in clinical medicine, from diagnostic to the prediction of hospital discharge [3], [4].

Recently, various AI algorithms have been applied to recommender systems helping them to enhance their medical device user experience and increase user satisfaction.

Compared to a conventional recommender system, AI-based recommendation systems provide a higher quality recommendation [5]. These systems provide advanced insights into determining the relationships between users and treatments, present more complex data interpretations, and discover comprehensive knowledge in terms of textual, visual, demographical, and contextual data. Advanced AI algorithms, when integrated into the clinical decision support system, can help doctors/clinicians in the identification of appropriate and timely interventions for a target patient.

Previous research on AI-based clinical decision support systems is mainly focused on imagology [6]–[12]. For example, in the case of oncology, clinicians use indicated pulmonary nodule areas on a radiographic image to guide endoscopists to localized early oesophageal squamous cell carcinoma [13]–[15]. Some studies have also explored the performance of AI models alone for the prediction of quality of life (QoL) indicators and life expectancies (survival analysis) in different patients [16]–[19]. Additionally, many literature reviews, addressing different features, algorithms, and challenges of recommender systems have been published in past [4], [20]–[25] and have demonstrated great scientific promise in terms of improved efficiency of treatment [26]–[34].

1.1 Aims and Objectives

With all the advancements in the field of big data, AI, and scientific research methodologies, there are still very few AI-based recommender systems being implemented/used by clinicians in the real-world [35]–[38]. This review provides detailed insight into different types of recommender systems, the capability of an AI-based recommender system to convert data into knowledge, and different evaluation matrices to determine the efficacy of a recommender system. In comparison to previously published reviews, shown in Table 1, this review contributes as:

- Systematically reviewing the most recent cutting-edge technologies (theoretical and practical) contributing to the field of AI-based recommender systems.
- Identifying the challenges in the way of real-time implementation of these recommender systems.
- Providing a brief discussion on the future of integration of AI algorithms in real-world medical devices for personalized healthcare systems.

Table 1 Comparison of recent review papers with the proposed review article

Title	Ref	Types of RS	Different AI Algorithms	AI in Healthcare settings	Performance Evaluation Matrices	Challenges	Acceptance of AI-based RS by Clinicians
Artificial intelligence in recommender systems	[5]	P	P	O	O	O	O
recommendation systems: Algorithms, challenges, metrics, and business opportunities	[39]	P	O	P	P	P	O
A review on deep learning for recommender systems: challenges and remedies	[40]	P	P	O	O	P	O
Artificial intelligence with multi-functional machine learning platform development for better healthcare and precision medicine	[41]	O	P	P	O	P	O

Reinforcement Learning-based Recommender Systems: A Survey	[42]	P	P	P	O	P	O
Proposed		**P**	**P**	**P**	**P**	**P**	**P**

The rest of the paper is organised as follows; Section 2 provides an overview of the search methodology and inclusion/exclusion criteria of the articles mentioned in this review. Section 3 describes the different types of recommender systems and a literature review of different clinical trials conducted for personalized healthcare. Section 4 reviews the different types of AI algorithms and their implementation as a recommender system, and different evaluation matrices used for evaluating the performance of the system. Discussion around challenges in the implementation of AI-based recommender systems and acceptance of such systems by clinicians is provided in Section 5. Lastly, Section 6 concludes the paper and provides future directions for researchers interested in this field.

2 Search Methodology

The search for the related literature was carried out following the PRISMA guidelines [43], [44], illustrated in Figure 1. The literature search was conducted on PubMed, Google Scholar, Web of Science, and IEEE digital library. The search terms were formed by combining two specific keywords (for example, Artificial Intelligence, Machine learning (ML), personalised treatment) and general keywords (for example, cardiology, neurology, oncology, cardio-oncology, and recommender systems). Initially, 7373 manuscripts were retrieved using different combinations of the above-mentioned keywords. The selection of literature for review was divided into two stages:

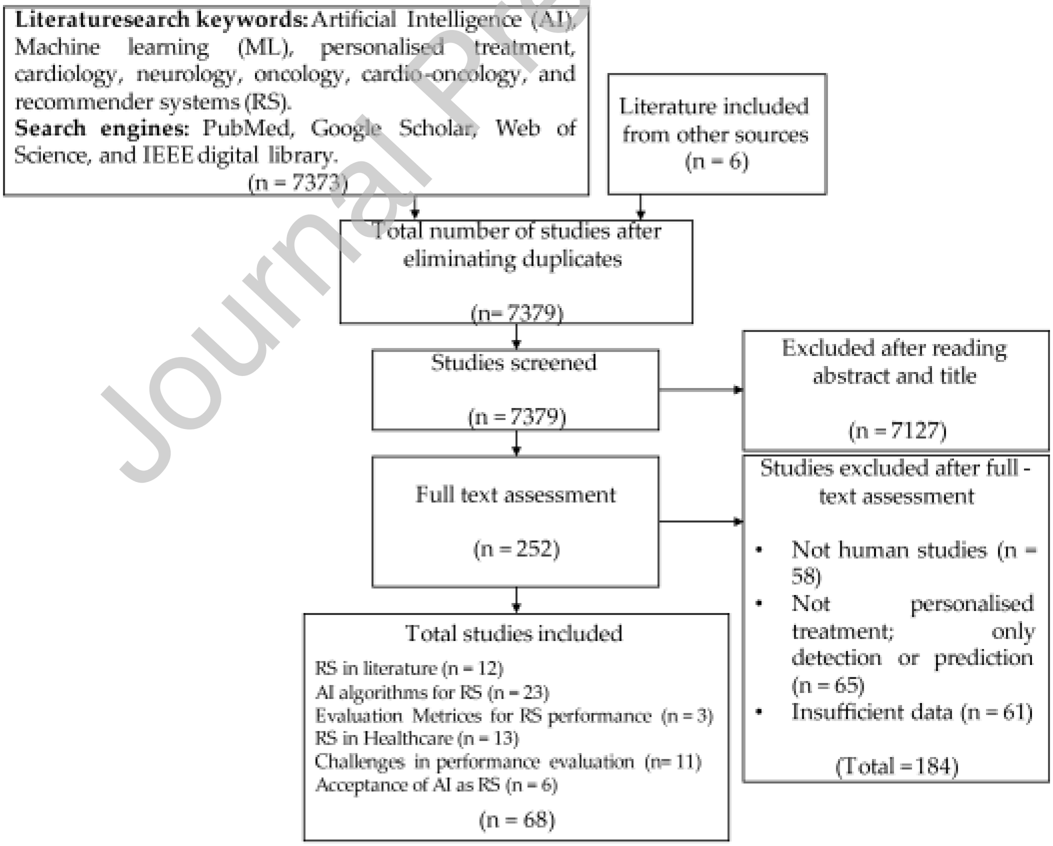

Figure 1 Adopted PRISMA guidelines and retrieved papers in this review

- In the first stage, studies related to AI/ML-based recommender systems for personalized treatment were included by reviewing the title and abstract of the papers. This resulted in the selection of 252 studies.
- In the second stage, a full-text assessment was performed and out of 252, 68 open-access articles were selected for further review. A detailed review of these 68 articles was performed to extract the related information and has been presented in this article.

3 Recommender Systems in the Literature

Recommender systems filter the data information in a personalised manner and suggest appropriate settings/content [45]. These systems generate recommendations and suggestions to assist the user in many critical decision-making processes. The recommender systems can be classified into three main categories; first, the content-based recommendation system generates recommendations of new settings based on similarities in the items/settings preferred previously by the same user. Second, a collaborative filtering recommendation system produces recommendations for a new user based on the preference of another user with similar choices. The third is a combination of the previous two approaches and is called a hybrid recommendation system. Each of the above-mentioned recommendation systems is briefly explained in the following subsections and is summarized in Figure 2.

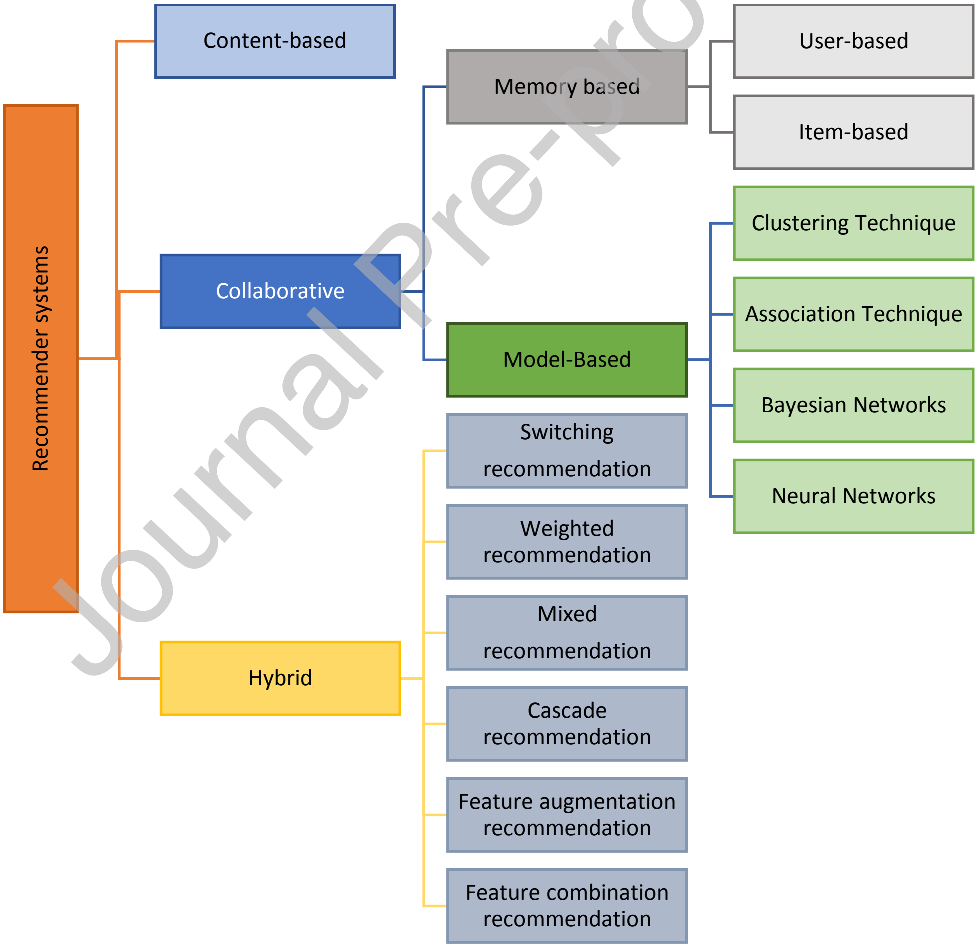

Figure 2 Classification of recommender systems presented in the literature

3.1 Content-based (CB) recommendation system

The main purpose of content-based recommender systems is to recommend settings/items that are previously preferred by the same user. These recommendations are based on the descriptive characteristics of items/settings and profiles of users [46]. The advantages of CB recommendation are three-fold [47], [48]. First, these recommendations are user-independent and are based on item/device representation. Thus, such systems do not suffer from data sparseness problems. Secondly, these systems recommend new settings to the user straightaway at the start, thus eliminating the cold-start problem. Finally, these systems clear explanation of recommendation results.

Along with the advantages, there are some limitations of the CB recommendation systems as well [47], [49], [50]. The major drawback of these systems includes the effectiveness of producing a personalized prediction for a specific user. Moreover, the recommendation produced by these systems lacks diversity and novelty as algorithms do not use community knowledge (settings used by similar item/device users).

3.2 Collaborative filtering (CF) recommendation system

Collaborative filtering recommendation systems are the most popular recommender systems for all the other systems [40], [51]. These systems generate the recommendation based on an assumption that if a group of users in a specific domain prefers one setting/item then a new user in the same domain might prefer the same settings as well. CF algorithms can be characterised into two categories [52]: Memory and model-based recommender systems.

Memory-based recommender algorithms use heuristic techniques to estimate the similarity value between the choice of users or items. Thus, is subdivided into user-based CF recommender systems and item-based CF recommender systems [53]. The CF recommender systems use the nearest-neighbour algorithm as its core algorithm. The recommendation is generated by calculating the ranks of different settings/items of a target user based on its neighbouring user's rating. This recommender system is simple to implement, effective and produces accurate recommendations but is not able to handle cold-start and un-popular settings that might get some rating and thus could come as recommended settings [49]. Alternatively, the model-based CF recommender system uses machine learning or data mining methods rather than heuristic techniques to predict a user's rating about a specific setting/item. This method was introduced to cover the shortcomings of memory-based recommender systems but has been significantly studied for other domains as well [54]. These systems provide the best recommendations if ancillary information is combined with the ranking matrix. This matrix factorization results in dimensionality reduction and scalability of the recommender system; acquisition of only relative rating results in higher recommendation accuracy and creates an improved user preference profile for better recommendation performance [55].

3.3 Hybrid recommendation system

Both content-based and collaborative-based recommender systems have unique strengths and weaknesses. Hybrid recommendation systems combine the strengths of CB and CF-based algorithms and avoid the drawbacks of each approach. Various hybridization methods have been proposed in the literature and are summarized as [40]; switching hybrid recommender selects a recommendation depending on the current situation from either algorithm. Weighted hybrid recommender produces output by combining scores of different approaches. A mixed hybrid recommender combines the output of switching and weighted approaches at the same time. A cascaded hybrid recommender provides recommendations produced by one approach and refined by another. Feature augmentation hybrid recommendation systems work as a recommendation of one approach is fed as input to other approaches. Lastly, the Feature combination hybrid recommender combines the features of both approaches and is utilized as a single algorithm.

4 Artificial Intelligence Algorithms for Recommender Systems

AI techniques have been developed to achieve automated intelligent systems covering the following six areas: knowledge engineering (understanding and processing knowledge), reasoning (problem-solving and logical conclusions), planning (setting and achieving a goal), communication (understanding natural language and translating it to human), perception (processing and analysing inputs/images/speeches), and motion (movement and manipulations)[5], [56]. In this section five main AI techniques are introduced and shown in Figure 3.

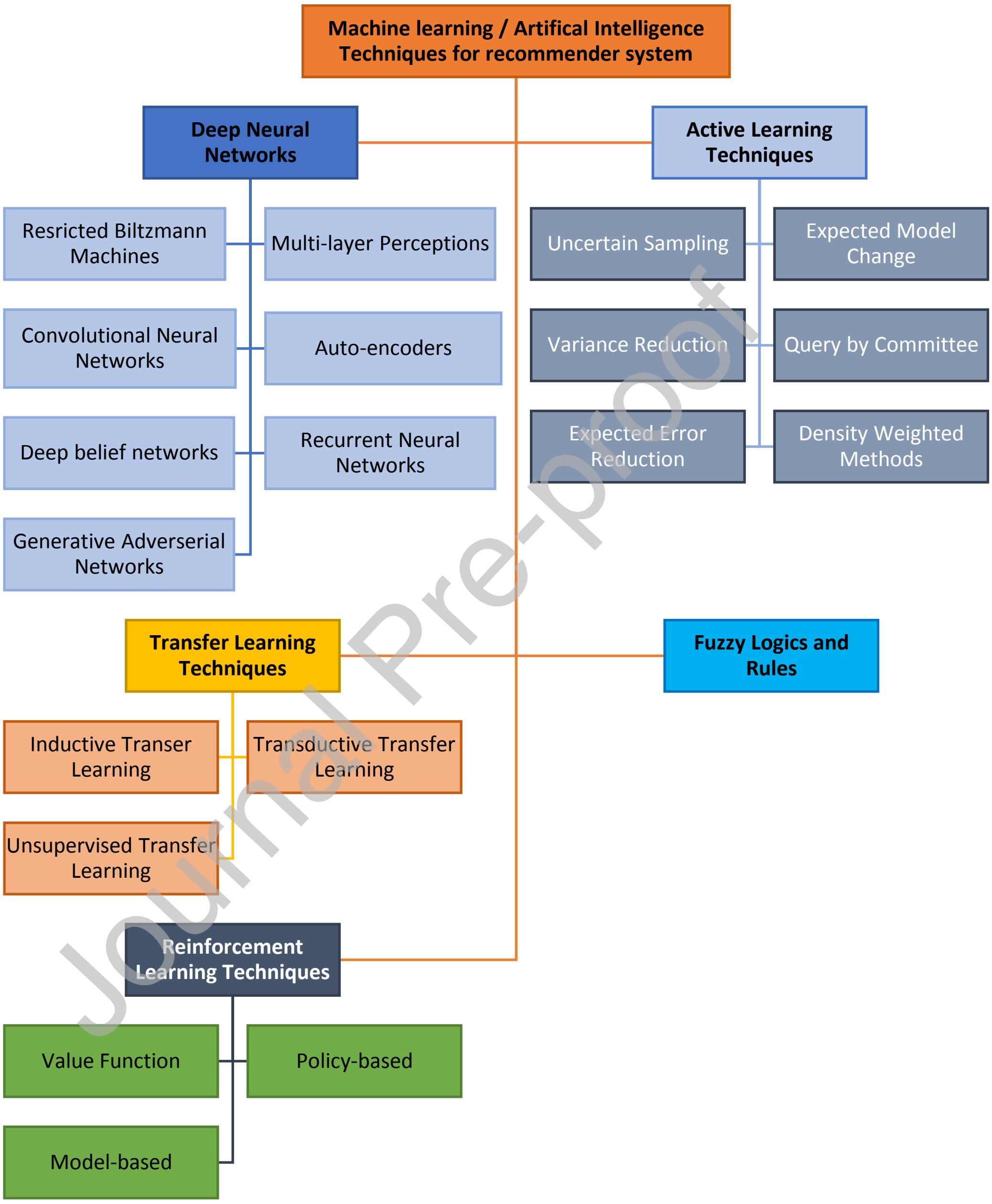

Figure 3 Taxonomy of Artificial Intelligence techniques used as a recommender system

4.1 Deep Neural Networks

Deep neural networks are inspired by human brain neurons. As recommendation tasks are concerned with the ranking/preference of settings by a user rather than classification, deep neural networks are rarely implemented as recommender systems. There are several types of deep neural networks [57]. Restricted Boltzmann Machines is a two-layered learning architecture where one layer is visible and corresponds to the components of the input (like pixels in an image) while the second layer is hidden and characterises dependencies between those components (intra-relationship of pixels*)* [58]–[60]. The multi-layer perceptions (MLPs) are fee-forward networks that consist of at least three or more layers with a non-linear activation function [61]. Convolutional neural networks (CNNs) are three-level networks i.e., an input layer, multiple hidden layers (convolutional, pooling, fully connected layers) and an output layer [62]. An *Auto-encoder* is an unsupervised machine-learning algorithm that learns the feature representations for dimensionality reduction, data diagnosis or data compression [63]. A deep belief network is a multi-layer architecture that uses a stack of restricted Boltzmann machines to obtain a deep hierarchical description of input data [58]. Recurrent Neural networks are intended to deal with sequential data using long short-term memory networks (LSTM). These networks are suitable for time-series data prediction [64], [65]. Generative Adversarial Networks (GANs) are the youngest in deep neural networks and are part of unsupervised machine learning algorithms. GANs are comprised of two networks i.e., Generator and Discriminator networks. Both networks compete to generate synthetic data that looks like the original data [66].

4.2 Active Learning Techniques

Active learning techniques have been introduced to facilitate the recommender systems in selecting the most preferred settings/items and suggesting them to the user for rating [67]. Active learning works on the principle of selective switching between training data and enabling machine learning for better performance with less information. These techniques can be subdivided into six groups based on their evaluation criteria for unlabelled data [68]. Uncertainty sampling evaluates the information which is least certain to get a rank. Expected model change considers information that causes the least changes to an already established model. Variance reduction measures the variance of the model and cuts it down to increase the stability of the model. Query by committee is a framework that minimizes the inconsistencies of queries to labelled data. Expected error reduction follows the variance reduction methods by calculating global error and reducing the potential risk of being considered as query information. Density-weighted methods look for representative information that is crucial in boundary decisions making.

4.3 Transfer Learning Techniques

Transfer learning exploits the correlation of multiple domains and extends the recommendation request from one domain with plentiful (source) data to multiple other domains with scarce (target) data [69]. It transfers the extracted knowledge of some specific settings preferred by one user to more source data to assist the learning task with target data. Transfer learning can be divided into three classes. First is inductive learning, where the target task is different from the source task [70]. Second is transductive learning, where both source and target tasks are the same, but domains are different [71]. The final category is unsupervised learning, which is the same as inductive learning except that there are no labels of data for both the source and target domain [72].

4.4 Fuzzy Logic and Rules

In the real world, information extraction and making recommendations based on specific data are uncertain and vague. Thus, using fuzzy logic/rules-based algorithms to handle these uncertainties and vagueness is the best option. Recommendations made by the fuzzy technique improve both regression and classification accuracies [73]. For content-based recommendations, these techniques profile the user and match appropriate settings/items [74]. For memory-based collaborative filtering (recommender) these theories profile the uncertain user preferences and match them with the best settings expected to be preferred by the user [75]. In model-based recommendation systems, different fuzzy models are implemented to alleviate the data sparsity and predict the best user-preferred settings [76].

4.5 Reinforced Learning Techniques

The nature of recommender systems is based on reinforcement learning techniques as the recommendation is an interactive process between the system and the user with a series of conditions and actions. Reinforced learning techniques aim to maximize the engagement of the user with the device and satisfy the users in the long term. The algorithm works by maximizing the reward of a sequence of actions to achieve a goal. Furthermore, the next input is affected by the action in an interactive way [77]. Reinforcement learning can be divided into value-function, policy-based learning, and model-based reinforcement learning [78].

5 Evaluation Metrics for Recommender Systems Performance

Typically, a recommender system performance is evaluated using precision and recall, F1-score, and accuracy matrices. Figure 4 shows the classification of performance metrics.

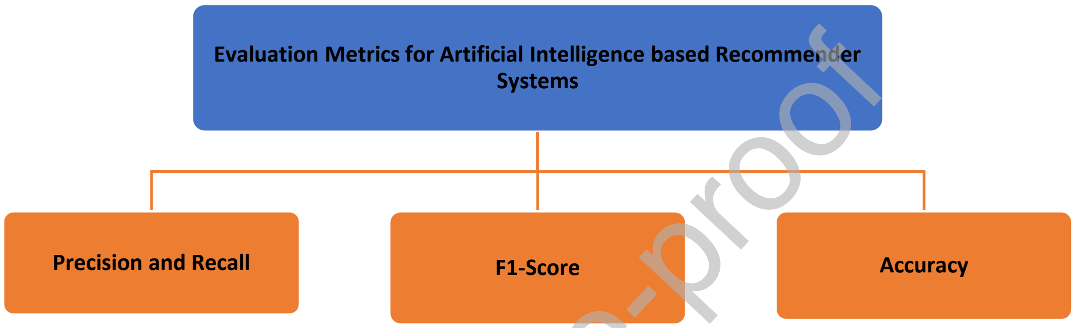

Figure 4 Performance evaluation matrices used for AI-based Recommender system

5.1.1 Precision and Recall

Precision and recall are two performance evaluation matrices where precision implies the number of preferred settings/items among all the recommended settings/items while recall is the number of preferred settings/items to the total number of settings/items that should be recommended and preferred [39]. Both these matrices are calculated using the confusion matrix as illustrated in Table 2.

Table 2 Confusion Matrix for calculation of Precision and Recall scores

	Successfully recommended	**Unsuccessfully recommended**
Recommended settings or items	*True Positive*	*False Positive*
Not recommended settings or items	*False Negative*	*True Negative*

Here *True Positive* indicates the number of settings/items that were originally recommended and were successfully adopted as preferred settings. *False Positive* represents the number of settings/items that were not successfully recommended by the recommender systems although they would have been preferred by the users. *False negative* denotes the number of disqualified settings/items recommended to the users by the systems while *True negative* refers to the number of settings/items that were labelled as not recommended and were also not preferred by the users. Mathematically, the precision and recall are calculated as:

$$Precision = \frac{True\ Postive}{True\ Positive + False\ Positive} \qquad (1)$$

$$Recall = \frac{True\ Positive}{True\ Positive + False\ Negative} \qquad (2)$$

The best recommender system will always try to optimize both matrices simultaneously by recommending fewer settings and getting them preferred each time.

5.1.2 F1-score

F1-score is an evaluation matric derived from precision and recall. F1-score can be defined as the number of recommendations needed to be made to detect the first failure [79]. Equation 3 shows the mathematical representation of the F1-score. The maximum value of the F1-score could be 1 suggesting all the predictions were accurate recommendations.

$$F1 - score = \frac{2 \times precision \times recall}{precision + recall} \qquad (3)$$

5.1.3 Accuracy

Accuracy is the prediction rating of a recommender system. Determining the accuracy of a recommender system is a complex task as there is no explicit technique to decide whether a recommendation is precise or not [80]. A system's recommendation accuracy is calculated using equation 4. Generally, accuracy is assessed by searching for low prediction errors by split-validation of known data and is performed offline.

$$Accuracy = \frac{number\ of\ recommendations\ preferred\ by\ user}{total\ recommendations\ made} \qquad (4)$$

6 Recommendation systems in the field of healthcare

In healthcare settings, recommender systems play a notable role in easing critical decision-making processes [39]. Several studies and clinical trials have been reported in the literature showing the use of recommender systems in healthcare settings. Thus, this section summarises reported recommender systems in the different fields of healthcare, illustrated in Figure 5.

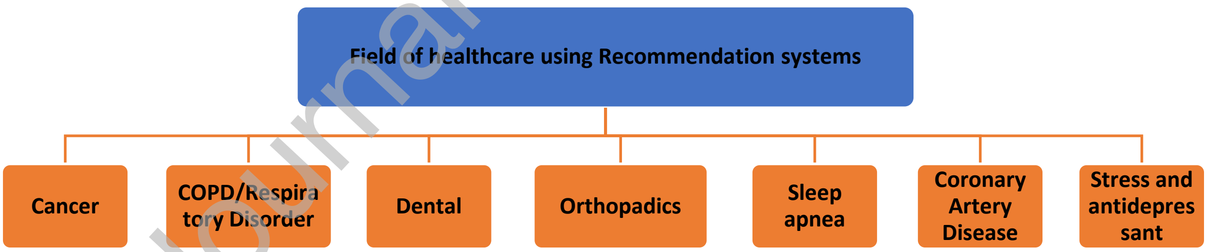

Figure 5 Healthcare domains utilizing recommendation systems for critical decision making

Table 3 presents a summary of clinical trials (literature) opting recommender system as an assistant in critical decision-making and providing in-time interventions for the last two years.

Table 3 Summary of literature adopting AI-based recommender systems in the field of healthcare

Title	Ref	Year	Objectives	Approach	Conclusion
Aid of a Machine Learning Algorithm Can Improve Clinician Predictions of Patient Quality of Life During Breast Cancer Treatments	[81]	2022	Measuring whether the integration of AI recommender in clinical decision-making improves the clinician's performance in predicting patients' quality of life (QoL) during treatment.	Experiment 1: 60 patients, 6 clinicians. Experiment 2: 90 patients, 9 clinicians. QoL evaluation at 6 and 12 months with and without AI prediction.	Accuracy at 6 months: Without AI: 69.6% With AI: 75.5% Accuracy at 12 months: Without AI: 70.9% With AI: 73.9% AI improved the overall performance of clinicians.
Perspectives on Machine Learning-Assisted Plasma	[82]	2022	Implementation of AI in the field of plasma medicine can provide	Quantification and real-time diagnostics of plasma medicine and	AI-based models assist and automate the CAP treatment. These models also help in the

Medicine: Toward Automated Plasma Treatment			safe, predictive, and reproducible cold atmospheric plasma (CAP) treatment.	prediction of treatment outcome.	prediction of treatment, real-time disease diagnosis and personalised treatment.
Artificial Intelligence Technology Combined with Ultrasound-Guided Needle Knife Interventional Treatment of PF: Improvement of Pain, Fascia Thickness, and Ankle-Foot Function in Patients	[83]	2022	Investigate the effect of AI combined with an ultrasound needle for the treatment of plantar fasciitis (PF).	130 patients were divided into a control group which received standard ultrasound-guided needle therapy and a study group that received AI-based ultrasound-guided needle therapy.	The patients in the study group reported a higher effective rate as compared to the control group (P<0.05). patients who received AI-based treatment indicated low pain levels, improved facia thickness and ankle-foot function.
Application of a Remotely Controlled Artificial Intelligence Analgesic Pump Device in Painless Treatment of Children	[84]	2022	Improvement of analgesic pump devices using remote-controlled AI for treatment of dental pulpitis in children.	100 children who were treated in the hospital were selected. 50 study children were given articaine and adrenaline mixed with AI-controlled anaesthesia. The Control group was only given articaine and adrenaline anaesthesia.	The pain score in intraoperative and anaesthesia in the study group was significantly lower than the control group (P<0.05). Furthermore, in a study group, 96.6% of patients were satisfied with the procedure as compared to 84.7% of control group patients.
Management and treatment of patients with obstructive sleep apnea using an intelligent monitoring system based on machine learning aiming to improve continuous positive airway pressure treatment compliance: randomized controlled trial	[85]	2021	Assess the effectiveness of AI-based monitoring systems for improved continuous positive airway pressure (CPAP) in obstructive sleep apnea patients	Anthropometric and clinical variables, sleepiness and QoL of 60 patients were recorded. AI-based mid-term CPAP compliance and rule-based recommendation app for patients and clinicians.	88% of the intervention patients were satisfied with the recommendations provided by the proposed (MiSAOS) app and they will continue using this app in future. Thus, AI-based intelligent system empowers patients in managing their chronic disease better.
How machine-learning recommendations influence clinician treatment selections: the example of antidepressant selection	[86]	2021	How clinicians' treatment decisions are influenced by AI-based recommendation in the domain of antidepressant selection.	Within-subject factorial experiment on 220 clinicians with patients' records. Tests were performed with and without AI-based recommendations and explanations.	There was no significant improvement in the selection of treatment by clinicians with and without AI recommendations. Moreover, the incorrect recommendation had an adverse effect on clinicians' selection of treatment and the explanation provided was insufficient to rely on an AI algorithm.
Cost-effectiveness of artificial intelligence monitoring for active tuberculosis treatment: A modeling study	[87]	2021	Evaluation of an AI-based AiCure platform that provides automated treatment monitoring of Tuberculosis (TB).	A Cost-effectiveness comparison of AiCure with standard directly observed therapy (DOT) was performed using the Markov model on 43 patients using AiCure and a control group of 71 patients on DOT.	The results of probabilistic sensitivity and deterministic analysis showed that for the average patient, the cost-effectiveness of AiCure is well dominant over standard DOT. DOT treatment costs $4,894 while AiCure cost $2668 with 0.02 improved quality-adjusted life years.
Application of Artificial Intelligence in Emergency Nursing of Patients with Chronic Obstructive Pulmonary Disease	[88]	2021	Application of AI in emergency centres of patients having chronic obstructive pulmonary disease (COPD).	A randomized trial with 447 patients divided into control and study group (patients received medicine based on AI recommendation).	COPD length of stay in hospital and overall hospitalizations were significantly less in the study group as compared to the control. QoL, psychological and emotional condition of study group patients was also better than the control group at a 12-month time.
Patients-centered SurvivorShIp care plan after Cancer treatments based on Big Data and Artificial Intelligence technologies (PERSIST): A	[89]	2021	Evaluate the impact of AI and big data analytics on the self-efficacy of cancer-survival patients following intervention supported by the mHealth application (digital tool).	The study involved 160 survivors. Each survival served as its control group (basal measurement obtained at the time of recruitment and 6-month follow-up).	The intervention delivered via the mHealth app increased self-efficacy, and overall satisfaction, and reduces distress about the outcome of the treatment and disease. It also improves cancer treatment and follow-up routines.

multicenter study protocol to evaluate efficacy of digital tools supporting cancer survivors					
Clinical integration of machine learning for curative-intent radiation treatment of patients with prostate cancer	[90]	2021	Evaluation of AI-based radiation therapy (RT) treatment planning for prostate cancer patients in clinical settings.	Clinicians and AI-generated RT treatment plans were deployed in retrospective simulation with 100 patients (divided into two groups, 50 each).	In a head-to-head comparison, 89% of AI-generated RT plans were selected as clinically acceptable as compared to only 72% of human-generated plans by treating physicians.
Artificial Intelligence Algorithm-Based Lumbar and Spinal MRI for Evaluation of Efficacy of Chinkuei Shin Chewan Decoction on Lumbar Spinal Stenosis	[91]	2021	Exploring the efficacy of chinkuei shin decoction (Chinese medicine for kidney) in the treatment of lumber spinal stenosis (LSS) using normal and AI-processed MRI images.	110 patients were divided into the control and study group. The Control group received the standard treatment while the study group was given chinkuei shin decoction medicine. The AI registration algorithm was implemented to introduce information entropy theory and was applied to MRI images.	The AI-based registration algorithm showed decreased noise levels (P<0.05), a dice value of 0.9 and a Jaccard value of 0.84 which was better than the 0.81 and 0.63 scores of traditional treatment. Thus, AI-based registration can evaluate the efficacy of LSS more prominently.
Screening cardiovascular autonomic neuropathy in diabetic patients with microvascular complications using machine learning: a 24-hour heart rate variability study	[92]	2021	Investigate the feasibility of 24-hour heart rate variability (HRV) monitoring embedded with AI algorithms to provide screening of patients with cardiovascular autonomic neuropathy (CAN).	HRV features were extracted from the HRV signal (every 5min) of 95 subjects. Four AI algorithms (support vector machine, random forest, convolutional neural network, and random under-sampling boosting) were used to predict the outcome of four tests. These test conditions were mimicking standard diagnostic procedures. Test 1: healthy or diabetic; test 2: any microvascular complication or not; test 3: the presence of CAN or not; test 4: check for multiple complications besides CAN.	The AI-based algorithms achieved high accuracies in determining the correct condition of the subject and helped in early screening of CAN stratifying the risk leading to sudden cardiac arrest. AI algorithms were able to predict with an accuracy of 85.5%, 98.5%, 98.3%, and 90.9% for test 1, test 2 test3 and test 4, respectively.
Personalized treatment for coronary artery disease patients: a machine learning approach	[93]	2020	Creation of a regression-based model to improve health outcomes for personalized treatment of coronary artery diseases.	Implementation of regression models (supervised machine learning) on electronic health records of 21460 patients.	AI-based model improved the prediction of potential adverse event expectation (with 82.35% accurate detections) and AI-based prescription improves the adverse event expectancy from 4.56 to 5.77 years by providing a better prescription.

7 Discussion and Insights

The recent development in the domain of recommender systems focuses on providing support for making critical decisions with proliferated information related to the metadata of user-contributed reviews. A recommender system is anticipated to provide recommendations that always meet the user requirements and gain a better understanding of the broad range of users' interests/preferences. There are several challenges associated with the performance evaluation of recommender systems that restrains the development of a state-of-the-art recommender system.

7.1 Challenges concerning performance evaluation of the recommender system

The most indicative measure of recommender systems performance is determined by user satisfaction. Although there is no heuristic formula to calculate user satisfaction, the performance of a recommender system could be determined by how it handles common issues (see Figure 6) like data sparsity, diversity, cold start, and scalability. This subsection discusses some of these issues and the performance of recommender systems against these issues.

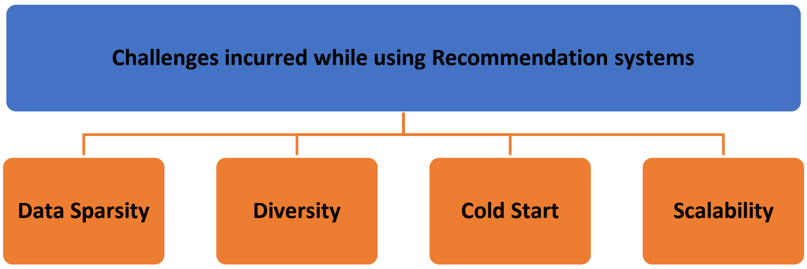

Figure 6 List of challenges incurred while using recommendation systems

7.1.1 Data Sparsity

Usually, users only intend to rank/provide feedback to limited settings/items. Thus, the reported user matrix has unknown ratings of different settings/items which leads to data sparsity problems [94]. Under this issue, the recommender system provides unreasonable recommendations to users who do not provide any rating or feedback. In literature, this issue is addressed by using techniques that utilises modelling based on users' behaviour and their trusted social connections [95], [96]. The robustness of recommender systems is significantly dependent on these trust values. Trust is defined as the belief in another's ability to provide accurate rankings/feedback ratings and is measured by the distance (in the unit of the number of arcs) connecting the two users [97].

7.1.2 Diversity

Diversity issue arises when the recommender systems suggest either similar settings/items or more diverse settings/items. An accurate recommender system provides recommendations based on differences instead of overlapping the user's preference. The diversity issue leaves the user with narrower selection options which might lead to negligence of highly related settings (that should have been recommended). The linear time closed itemset miner (LCM) technique can increase the diversity of a recommender system by finding efficient frequent settings or item sets [98]. One concern is that if the algorithm focuses on enhancing the diversity of recommendations, the accuracy of the systems could be lost [99]. Thus, the accuracy threshold should always be preserved while dealing with diversity issues.

7.1.3 Cold Start

The cold start problem always exists for existing or new users. The recommender system does not perform optimally when no or insufficient metadata (information) is available. The cold-start problem occurs when a user creates a new account and does not have any preferences history on which to base a recommendation. Cold start can be divided into two subsets: user cold start and product cold start [100]. To mitigate this issue, naïve Bayes techniques are implemented [100]. In this technique, different characteristics of settings/items are supposed to be mutually independent thus characteristics of new settings/items can be estimated even if it is not found in the training set. Naïve Bayes methods are simple to implement and have proven to be the most accurate way to eliminate the cold start problem [101].

7.1.4 Scalability

Modern recommender systems are required to process a lot of information and generate quick recommendations. A recommendation system can search many potential possibilities in real-time, but the algorithm experiences performance issues for users with an abundance of information [96] which leads to the scalability problem. Commonly, one-dimensionality reduction techniques are used to reduce this problem [102], [103]. These techniques use the clustering method and provide two significant benefits. First, it eliminates the sparsity of the dataset and secondly, it divides the available data into smaller parts to speed up prediction and recommendation [104].

7.2 Acceptance of Artificial Intelligence as a recommender system

In the field of healthcare, several AI-based models have already been implemented in real-world clinical settings and have a significant impact on patient care [35]–[38]. Although the growing importance and relevance of AI in the field of healthcare is indisputable, it is important to develop an intelligent framework that connects analytical and operational healthcare systems. This will improve clinical practice and will allow experts from different domains to perform predictive and measurement analyses. Based on the reviewed literature, AI has the potential to play a significant role in clinical operations, analytics, and research to improve individualized as well as population healthcare systems. AI-based recommender systems can provide healthcare facilities with a low-cost solution and provide clinicians/staff with a reduced work burden [41].

Several factors limit the effective implementation of AI-based recommender systems in healthcare systems [105]–[108]. Some of these factors are listed as follows:

1. Availability of low-quality and limited data.
2. Privacy issues are bounded by data collection, sharing and usage.
3. Disruption in the patient-clinician relationship
4. Lack of evidence and reproducibility of AI-based models
5. Selection of best machine learning algorithm
6. Lack of understanding of AI model process and prediction
7. Job insecurity
8. The threat of dehumanization of patient data
9. Impartial access and conflict of interest
10. Sanity checks for minimization of bias and handling of erroneous results.
11. Exploration of accountability of AI-based recommendations
12. Ethics, consent, and ownership of the collected data

The medical community needs to formulate widely accepted standards to eradicate the lack of sufficient (high-quality) clinical data. The data-gathering procedures must also be standardized to ensure that data collection is relevant to specific clinical applications. Furthermore, easy-to-use AI-based tools/models must be proposed to ease their use by non-expert clinicians. Lastly, as complex protocols and complicated models/devices are unlikely to achieve the interest of people (who are not specialized), the simplification of data procurement and control systems is also of critical importance to provide improved point-of-care treatments using these AI-based systems. All the above-mentioned challenges can be eradicated only through the coordinated efforts of researchers, data scientists, and clinicians/physicians.

8 Conclusions and future directions

The current recommender systems emphasise on providing support in critical decision-making with extensive information related to user-contributed reviews. The integration of advanced AI algorithms into clinical decision-making systems can provide clinicians with crucial information about a target patient, thereby ensuring the patient will receive suitable and timely interventions. The proposed survey aimed to review the existing literature on recommender systems specifically in the field of healthcare to help the researchers build a comprehensive understanding of this field.

In this paper, a detailed review of the different recommender systems reported in the literature has been presented. Recommender systems are broadly divided into three types i.e., content-based, collaborative filtering and hybrid recommender system. Collaborative filtering is further divided into memory-based and model-based recommender systems while hybrid recommender systems have six sub-categories. The review also describes different artificial intelligence algorithms such as deep neural networks, active learning, transfer learning, fuzzy logic, and reinforcement learning and their implementation as recommender systems in the field of healthcare. Furthermore, standard evaluation matrices and challenges incurred by performance evaluation are also discussed. Finally, a brief discussion about the acceptance of AI-based recommender systems in healthcare is provided.

From the review it could be concluded that the trend of providing personalized healthcare is fast growing, thus the research on recommender systems plays a vital role in information filtering and health-related recommendations. Until a perfect recommender system is developed, the influence of the clinician should always be considered in final decision-making when evaluating the performance of the recommender system. Moreover, the application of AI algorithms does provide promising and encouraging results, but challenges such as scalability, accuracy, data sparsity, cold-start, and diversity are still open for improvement and demand further work. Further, as recommender systems become more prevalent in healthcare, it is important to consider the ethical implications of their use. Future research should also focus on developing ethical frameworks for recommender systems in healthcare, which prioritize patient privacy, safety and autonomy.

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References

[1] J. Beel, S. Langer, M. Genzmehr, B. Gipp, C. Breitinger, and A. Nürnberger, "Research paper recommender system evaluation: a quantitative literature survey," in *Proceedings of the International Workshop on Reproducibility and Replication in Recommender Systems Evaluation*, 2013, pp. 15–22.

[2] F. Ricci, L. Rokach, and B. Shapira, "Introduction to recommender systems handbook," in *Recommender systems handbook*, Springer, 2011, pp. 1–35.

[3] S. Sivapalan, A. Sadeghian, H. Rahnama, and A. M. Madni, "Recommender systems in e-commerce," in *2014 World Automation Congress (WAC)*, 2014, pp. 179–184.

[4] J. Lu, D. Wu, M. Mao, W. Wang, and G. Zhang, "Recommender system application developments: a survey," *Decis. Support Syst.*, vol. 74, pp. 12–32, 2015.

[5] Q. Zhang, J. Lu, and Y. Jin, "Artificial intelligence in recommender systems," *Complex \& Intell. Syst.*, vol. 7, no. 1, pp. 439–457, 2021.

[6] D. F. Steiner *et al.*, "Impact of deep learning assistance on the histopathologic review of lymph nodes for metastatic breast cancer," *Am. J. Surg. Pathol.*, vol. 42, no. 12, p. 1636, 2018.

[7] A. Kiani *et al.*, "Impact of a deep learning assistant on the histopathologic classification of liver cancer," *NPJ Digit. Med.*, vol. 3, no. 1, pp. 1–8, 2020.

[8] L. Wu *et al.*, "Randomised controlled trial of WISENSE, a real-time quality improving system for monitoring blind spots during esophagogastroduodenoscopy," *Gut*, vol. 68, no. 12, pp. 2161–2169, 2019.

[9] P. Wang *et al.*, "Real-time automatic detection system increases colonoscopic polyp and adenoma detection rates: a prospective randomised controlled study," *Gut*, vol. 68, no. 10, pp. 1813–1819, 2019.

[10] J.-R. Su *et al.*, "Impact of a real-time automatic quality control system on colorectal polyp and adenoma detection: a prospective randomized controlled study (with videos)," *Gastrointest. Endosc.*, vol. 91, no. 2, pp. 415–424, 2020.

[11] Y. Sim *et al.*, “Deep convolutional neural network--based software improves radiologist detection of malignant lung nodules on chest radiographs,” *Radiology*, vol. 294, no. 1, pp. 199–209, 2020.
[12] K. H. Cha *et al.*, “Diagnostic accuracy of CT for prediction of bladder cancer treatment response with and without computerized decision support,” *Acad. Radiol.*, vol. 26, no. 9, pp. 1137–1145, 2019.
[13] T. Kozuka *et al.*, “Efficiency of a computer-aided diagnosis (CAD) system with deep learning in detection of pulmonary nodules on 1-mm-thick images of computed tomography,” *Jpn. J. Radiol.*, vol. 38, no. 11, pp. 1052–1061, 2020.
[14] S. Jang *et al.*, “Deep Learning--based Automatic Detection Algorithm for Reducing Overlooked Lung Cancers on Chest Radiographs,” *Radiology*, vol. 302, no. 2, pp. E10--E10, 2022.
[15] S.-L. Cai *et al.*, “Using a deep learning system in endoscopy for screening of early esophageal squamous cell carcinoma (with video),” *Gastrointest. Endosc.*, vol. 90, no. 5, pp. 745–753, 2019.
[16] M. Savić *et al.*, “Analysis of Machine Learning Models Predicting Quality of Life for Cancer Patients,” in *Proceedings of the 13th International Conference on Management of Digital EcoSystems*, 2021, pp. 35–42.
[17] K. Kourou *et al.*, “A machine learning-based pipeline for modeling medical, socio-demographic, lifestyle and self-reported psychological traits as predictors of mental health outcomes after breast cancer diagnosis: An initial effort to define resilience effects,” *Comput. Biol. Med.*, vol. 131, p. 104266, 2021.
[18] Y. H. Liu, J. Jin, and Y. J. Liu, “Machine learning--based random forest for predicting decreased quality of life in thyroid cancer patients after thyroidectomy,” *Support. Care Cancer*, vol. 30, no. 3, pp. 2507–2513, 2022.
[19] J. Sim *et al.*, “The major effects of health-related quality of life on 5-year survival prediction among lung cancer survivors: applications of machine learning,” *Sci. Rep.*, vol. 10, no. 1, pp. 1–12, 2020.
[20] J. Bobadilla, F. Ortega, A. Hernando, and A. Gutiérrez, “Recommender systems survey,” *Knowledge-based Syst.*, vol. 46, pp. 109–132, 2013.
[21] X. Yang, Y. Guo, Y. Liu, and H. Steck, “A survey of collaborative filtering based social recommender systems,” *Comput. Commun.*, vol. 41, pp. 1–10, 2014.
[22] Z. Ding, X. Li, C. Jiang, and M. Zhou, “Objectives and state-of-the-art of location-based social network recommender systems,” *Acm Comput. Surv.*, vol. 51, no. 1, pp. 1–28, 2018.
[23] F. Ricci, L. Rokach, and B. Shapira, “Recommender systems: introduction and challenges,” in *Recommender systems handbook*, Springer, 2015, pp. 1–34.
[24] C. C. Aggarwal, “An introduction to recommender systems,” in *Recommender systems*, Springer, 2016, pp. 1–28.
[25] T. Iqbal, A. Elahi, W. Wijns, and A. Shahzad, “Exploring Unsupervised Machine Learning Classification Methods for Physiological Stress Detection,” *Front. Med. Technol.*, vol. 4, 2022.
[26] X. Liu *et al.*, “A comparison of deep learning performance against health-care professionals in detecting diseases from medical imaging: a systematic review and meta-analysis,” *lancet Digit. Heal.*, vol. 1, no. 6, pp. e271--e297, 2019.
[27] M. Nagendran *et al.*, “Artificial intelligence versus clinicians: systematic review of design, reporting standards, and claims of deep learning studies,” *bmj*, vol. 368, 2020.
[28] S. Shilo, H. Rossman, and E. Segal, “Axes of a revolution: challenges and promises of big data in healthcare,” *Nat. Med.*, vol. 26, no. 1, pp. 29–38, 2020.
[29] S. M. McKinney *et al.*, “International evaluation of an AI system for breast cancer screening,” *Nature*, vol. 577, no. 7788, pp. 89–94, 2020.
[30] D. Ardila *et al.*, “End-to-end lung cancer screening with three-dimensional deep learning on low-dose chest computed tomography,” *Nat. Med.*, vol. 25, no. 6, pp. 954–961, 2019.
[31] A. Esteva *et al.*, “Dermatologist-level classification of skin cancer with deep neural networks,” *Nature*, vol. 542, no. 7639, pp. 115–118, 2017.
[32] A. Y. Hannun *et al.*, “Cardiologist-level arrhythmia detection and classification in ambulatory electrocardiograms using a deep neural network,” *Nat. Med.*, vol. 25, no. 1, pp. 65–69, 2019.
[33] S. L. Hyland *et al.*, “Early prediction of circulatory failure in the intensive care unit using machine learning,” *Nat. Med.*, vol. 26, no. 3, pp. 364–373, 2020.
[34] T. Iqbal, A. Elahi, W. Wijns, B. Amin, and A. Shahzad, “Improved Stress Classification Using Automatic Feature Selection from Heart Rate and Respiratory Rate Time Signals,” *Appl. Sci.*, vol. 13, no. 5, p. 2950, 2023.
[35] T. C. Hollon *et al.*, “Near real-time intraoperative brain tumor diagnosis using stimulated Raman histology and deep neural networks,” *Nat. Med.*, vol. 26, no. 1, pp. 52–58, 2020.
[36] R. E. McCarroll *et al.*, “Retrospective validation and clinical implementation of automated contouring of organs at risk in the head and neck: a step toward automated radiation treatment planning for low-and middle-income countries,” *J. Glob. Oncol.*, vol. 4, pp. 1–11, 2018.
[37] M. Wijnberge *et al.*, “Effect of a machine learning--derived early warning system for intraoperative hypotension vs standard care on depth and duration of intraoperative hypotension during elective noncardiac surgery: the HYPE randomized clinical trial,” *Jama*, vol. 323, no. 11, pp. 1052–1060, 2020.
[38] R. Nimri *et al.*, “Insulin dose optimization using an automated artificial intelligence-based decision support system in youths with type 1 diabetes,” *Nat. Med.*, vol. 26, no. 9, pp. 1380–1384, 2020.
[39] Z. Fayyaz, M. Ebrahimian, D. Nawara, A. Ibrahim, and R. Kashef, “Recommendation systems: Algorithms, challenges, metrics, and business opportunities,” *Appl. Sci.*, vol. 10, no. 21, p. 7748, 2020.
[40] Z. Batmaz, A. Yurekli, A. Bilge, and C. Kaleli, “A review on deep learning for recommender systems: challenges and remedies,” *Artif. Intell. Rev.*, vol. 52, no. 1, pp. 1–37, 2019.
[41] Z. Ahmed, K. Mohamed, S. Zeeshan, and X. Dong, “Artificial intelligence with multi-functional machine learning platform development for better healthcare and precision medicine,” *Database*, vol. 2020, 2020.
[42] M. M. Afsar, T. Crump, and B. Far, “Reinforcement Learning based Recommender Systems: A Survey,” *ACM*

Comput. Surv., 2022.
[43] PRISMA, “Welcome to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) website!” PRISMA Ottawa, ON, Canada, 2015.
[44] D. Moher, A. Liberati, J. Tetzlaff, D. G. Altman, and P. Group, “Preferred reporting items for systematic reviews and meta-analyses: the PRISMA statement,” *PLoS Med.*, vol. 6, no. 7, p. e1000097, 2009.
[45] J. Ben Schafer, J. A. Konstan, and J. Riedl, “E-commerce recommendation applications,” *Data Min. Knowl. Discov.*, vol. 5, no. 1, pp. 115–153, 2001.
[46] R. Van Meteren and M. Van Someren, “Using content-based filtering for recommendation,” in *Proceedings of the machine learning in the new information age: MLnet/ECML2000 workshop*, 2000, vol. 30, pp. 47–56.
[47] P. Lops, M. de Gemmis, and G. Semeraro, “Content-based recommender systems: State of the art and trends,” *Recomm. Syst. Handb.*, pp. 73–105, 2011.
[48] Q. Shambour and J. Lu, “A trust-semantic fusion-based recommendation approach for e-business applications,” *Decis. Support Syst.*, vol. 54, no. 1, pp. 768–780, 2012.
[49] G. Adomavicius and A. Tuzhilin, “Toward the next generation of recommender systems: A survey of the state-of-the-art and possible extensions,” *IEEE Trans. Knowl. Data Eng.*, vol. 17, no. 6, pp. 734–749, 2005.
[50] M. Balabanović and Y. Shoham, “Fab: content-based, collaborative recommendation,” *Commun. ACM*, vol. 40, no. 3, pp. 66–72, 1997.
[51] H. Liu, Z. Hu, A. Mian, H. Tian, and X. Zhu, “A new user similarity model to improve the accuracy of collaborative filtering,” *Knowledge-based Syst.*, vol. 56, pp. 156–166, 2014.
[52] X. Su and T. M. Khoshgoftaar, “A survey of collaborative filtering techniques,” *Adv. Artif. Intell.*, vol. 2009, 2009.
[53] D. Li, Q. Lv, L. Shang, and N. Gu, “Item-based top-N recommendation resilient to aggregated information revelation,” *Knowledge-Based Syst.*, vol. 67, pp. 290–304, 2014.
[54] Y. Shi, M. Larson, and A. Hanjalic, “Collaborative filtering beyond the user-item matrix: A survey of the state of the art and future challenges,” *ACM Comput. Surv.*, vol. 47, no. 1, pp. 1–45, 2014.
[55] B. Liu, H. Xiong, S. Papadimitriou, Y. Fu, and Z. Yao, “A general geographical probabilistic factor model for point of interest recommendation,” *IEEE Trans. Knowl. Data Eng.*, vol. 27, no. 5, pp. 1167–1179, 2014.
[56] S. P. Yadav, D. P. Mahato, and N. T. D. Linh, *Distributed artificial intelligence: A modern approach*. CRC Press, 2020.
[57] Y. LeCun, Y. Bengio, and G. Hinton, “Deep learning,” *Nature*, vol. 521, no. 7553, pp. 436–444, 2015.
[58] G. E. Hinton, “Deep belief networks,” *Scholarpedia*, vol. 4, no. 5, p. 5947, 2009.
[59] D. C. Cire\csan, U. Meier, L. M. Gambardella, and J. Schmidhuber, “Deep, big, simple neural nets for handwritten digit recognition,” *Neural Comput.*, vol. 22, no. 12, pp. 3207–3220, 2010.
[60] T. Iqbal, H. Ali, M. M. Saad, S. Khan, and C. Tanougast, “Capsule-net for Urdu digits recognition,” in *Proceedings of the 2019 10th IEEE International Conference on Intelligent Data Acquisition and Advanced Computing Systems: Technology and Applications, IDAACS 2019*, 2019, vol. 1.
[61] F. Murtagh, “Multilayer perceptrons for classification and regression,” *Neurocomputing*, vol. 2, no. 5–6, pp. 183–197, 1991.
[62] H. Ali, A. Ullah, T. Iqbal, and S. Khattak, “Pioneer dataset and automatic recognition of Urdu handwritten characters using a deep autoencoder and convolutional neural network,” *SN Appl. Sci.*, vol. 2, no. 2, pp. 1–12, 2020.
[63] Y. Wang, H. Yao, and S. Zhao, “Auto-encoder based dimensionality reduction,” *Neurocomputing*, vol. 184, pp. 232–242, 2016.
[64] M. M. Saad, T. Iqbal, H. Ali, M. F. Bulbul, S. Khan, and C. Tanougast, “Incident Detection over Unified Threat Management Platform on a Cloud Network,” in *Proceedings of the 2019 10th IEEE International Conference on Intelligent Data Acquisition and Advanced Computing Systems: Technology and Applications, IDAACS 2019*, 2019, vol. 2.
[65] D. E. Rumelhart, G. E. Hinton, and R. J. Williams, “Learning representations by back-propagating errors,” *Nature*, vol. 323, no. 6088, pp. 533–536, 1986.
[66] T. Iqbal and H. Ali, “Generative Adversarial Network for Medical Images (MI-GAN),” *J. Med. Syst.*, vol. 42, no. 11, 2018.
[67] M. Elahi, F. Ricci, and N. Rubens, “A survey of active learning in collaborative filtering recommender systems,” *Comput. Sci. Rev.*, vol. 20, pp. 29–50, 2016.
[68] A. Krishnakumar, “Active learning literature survey,” *Tech. rep., Tech. reports, Univ. California, St. Cruz.*, vol. 42, 2007.
[69] J. Lu, H. Zuo, and G. Zhang, “Fuzzy multiple-source transfer learning,” *IEEE Trans. Fuzzy Syst.*, vol. 28, no. 12, pp. 3418–3431, 2019.
[70] Z. Kang, K. Grauman, and F. Sha, “Learning with whom to share in multi-task feature learning,” in *ICML*, 2011.
[71] A. Arnold, R. Nallapati, and W. W. Cohen, “A comparative study of methods for transductive transfer learning,” in *Seventh IEEE international conference on data mining workshops (ICDMW 2007)*, 2007, pp. 77–82.
[72] M. Ding, J. Tang, and J. Zhang, “Semi-supervised learning on graphs with generative adversarial nets,” in *Proceedings of the 27th ACM International Conference on Information and Knowledge Management*, 2018, pp. 913–922.
[73] J. A. Roubos, M. Setnes, and J. Abonyi, “Learning fuzzy classification rules from labeled data,” *Inf. Sci. (Ny).*, vol. 150, no. 1–2, pp. 77–93, 2003.
[74] R. R. Yager, “Fuzzy logic methods in recommender systems,” *Fuzzy Sets Syst.*, vol. 136, no. 2, pp. 133–149, 2003.
[75] Z. Zhang, H. Lin, K. Liu, D. Wu, G. Zhang, and J. Lu, “A hybrid fuzzy-based personalized recommender system for telecom products/services,” *Inf. Sci. (Ny).*, vol. 235, pp. 117–129, 2013.
[76] M. Nilashi, O. bin Ibrahim, and N. Ithnin, “Multi-criteria collaborative filtering with high accuracy using higher

order singular value decomposition and Neuro-Fuzzy system," *Knowledge-Based Syst.*, vol. 60, pp. 82–101, 2014.
[77] R. S. Sutton and A. G. Barto, *Reinforcement learning: An introduction*. MIT press, 2018.
[78] T. M. Moerland, J. Broekens, and C. M. Jonker, "Model-based reinforcement learning: A survey," *arXiv Prepr. arXiv2006.16712*, 2020.
[79] J. A. Hanley and B. J. McNeil, "The meaning and use of the area under a receiver operating characteristic (ROC) curve.," *Radiology*, vol. 143, no. 1, pp. 29–36, 1982.
[80] S. Vaishnavi, A. Jayanthi, and S. Karthik, "Ranking technique to improve diversity in recommender systems," *Int. J. Comput. Appl.*, vol. 68, no. 2, 2013.
[81] M. Nuutinen *et al.*, "Aid of a Machine Learning Algorithm Can Improve Clinician Predictions of Patient Quality of Life During Breast Cancer Treatments."
[82] A. D. Bonzanini, K. Shao, A. Stancampiano, D. B. Graves, and A. Mesbah, "Perspectives on Machine Learning-Assisted Plasma Medicine: Toward Automated Plasma Treatment," *IEEE Trans. Radiat. Plasma Med. Sci.*, vol. 6, no. 1, pp. 16–32, 2021.
[83] S. Zhu, Y. Niu, J. Wang, D. Xu, and Y. Li, "Artificial Intelligence Technology Combined with Ultrasound-Guided Needle Knife Interventional Treatment of PF: Improvement of Pain, Fascia Thickness, and Ankle-Foot Function in Patients," *Comput. Math. Methods Med.*, vol. 2022, 2022.
[84] F. Zhang, S. Wu, M. Qu, and L. Zhou, "Application of a Remotely Controlled Artificial Intelligence Analgesic Pump Device in Painless Treatment of Children," *Contrast Media \& Mol. Imaging*, vol. 2022, 2022.
[85] C. Turino *et al.*, "Management and treatment of patients with obstructive sleep apnea using an intelligent monitoring system based on machine learning aiming to improve continuous positive airway pressure treatment compliance: randomized controlled trial," *J. Med. Internet Res.*, vol. 23, no. 10, p. e24072, 2021.
[86] M. Jacobs, M. F. Pradier, T. H. McCoy, R. H. Perlis, F. Doshi-Velez, and K. Z. Gajos, "How machine-learning recommendations influence clinician treatment selections: the example of antidepressant selection," *Transl. Psychiatry*, vol. 11, no. 1, pp. 1–9, 2021.
[87] J. Salcedo, M. Rosales, J. S. Kim, D. Nuno, S. Suen, and A. H. Chang, "Cost-effectiveness of artificial intelligence monitoring for active tuberculosis treatment: A modeling study," *PLoS One*, vol. 16, no. 7, p. e0254950, 2021.
[88] L. Hong, X. Cheng, and D. Zheng, "Application of Artificial Intelligence in Emergency Nursing of Patients with Chronic Obstructive Pulmonary Disease," *Contrast Media \& Mol. Imaging*, vol. 2021, 2021.
[89] I. Mlakar *et al.*, "Patients-centered SurvivorShIp care plan after Cancer treatments based on Big Data and Artificial Intelligence technologies (PERSIST): A multicenter study protocol to evaluate efficacy of digital tools supporting cancer survivors," *BMC Med. Inform. Decis. Mak.*, vol. 21, no. 1, pp. 1–14, 2021.
[90] C. McIntosh *et al.*, "Clinical integration of machine learning for curative-intent radiation treatment of patients with prostate cancer," *Nat. Med.*, vol. 27, no. 6, pp. 999–1005, 2021.
[91] Y. Zhu *et al.*, "Artificial Intelligence Algorithm-Based Lumbar and Spinal MRI for Evaluation of Efficacy of Chinkuei Shin Chewan Decoction on Lumbar Spinal Stenosis," *Contrast Media \& Mol. Imaging*, vol. 2021, 2021.
[92] M. Alkhodari *et al.*, "Screening cardiovascular autonomic neuropathy in diabetic patients with microvascular complications using machine learning: a 24-hour heart rate variability study," *IEEE Access*, vol. 9, pp. 119171–119187, 2021.
[93] D. Bertsimas, A. Orfanoudaki, and R. B. Weiner, "Personalized treatment for coronary artery disease patients: a machine learning approach," *Health Care Manag. Sci.*, vol. 23, no. 4, pp. 482–506, 2020.
[94] N. F. Al-Bakri and S. H. Hashim, "Reducing data sparsity in recommender systems," *Al-Nahrain J. Sci.*, vol. 21, no. 2, pp. 138–147, 2018.
[95] G. Guo, "Integrating trust and similarity to ameliorate the data sparsity and cold start for recommender systems," in *Proceedings of the 7th ACM conference on Recommender systems*, 2013, pp. 451–454.
[96] G. Guo, J. Zhang, and D. Thalmann, "Merging trust in collaborative filtering to alleviate data sparsity and cold start," *Knowledge-Based Syst.*, vol. 57, pp. 57–68, 2014.
[97] P. Massa and P. Avesani, "Trust-aware recommender systems," in *Proceedings of the 2007 ACM conference on Recommender systems*, 2007, pp. 17–24.
[98] M. B. Karanam, "Tackling the problems of diversity in recommender systems," Kansas State University, 2010.
[99] T. Zhou, Z. Kuscsik, J.-G. Liu, M. Medo, J. R. Wakeling, and Y.-C. Zhang, "Solving the apparent diversity-accuracy dilemma of recommender systems," *Proc. Natl. Acad. Sci.*, vol. 107, no. 10, pp. 4511–4515, 2010.
[100] T. N. Lillegraven and A. C. Wolden, "Design of a bayesian recommender system for tourists presenting a solution to the cold-start user problem," Institutt for datateknikk og informasjonsvitenskap, 2010.
[101] Z. Gantner, L. Drumond, C. Freudenthaler, S. Rendle, and L. Schmidt-Thieme, "Learning attribute-to-feature mappings for cold-start recommendations," in *2010 IEEE International Conference on Data Mining*, 2010, pp. 176–185.
[102] G. Takács, I. Pilászy, B. Németh, and D. Tikk, "Scalable collaborative filtering approaches for large recommender systems," *J. Mach. Learn. Res.*, vol. 10, pp. 623–656, 2009.
[103] B. Sarwar, G. Karypis, J. Konstan, and J. Riedl, "Incremental singular value decomposition algorithms for highly scalable recommender systems," in *Fifth international conference on computer and information science*, 2002, vol. 1, no. 012002, pp. 27–28.
[104] B. M. Sarwar, G. Karypis, J. Konstan, and J. Riedl, "Recommender systems for large-scale e-commerce: Scalable neighborhood formation using clustering," in *Proceedings of the fifth international conference on computer and information technology*, 2002, vol. 1, pp. 291–324.
[105] K. Kourou, T. P. Exarchos, K. P. Exarchos, M V Karamouzis, and D. I. Fotiadis, "Machine learning applications in cancer prognosis and prediction," *Comput. Struct. Biotechnol. J.*, vol. 13, pp. 8–17, 2015.
[106] S. P. Prabhu, "Ethical challenges of machine learning and deep learning algorithms.," *Lancet. Oncol.*, vol. 20, no. 5,

pp. 621–622, 2019.
[107] S. H. Park, Y.-H. Kim, J. Y. Lee, S. Yoo, and C. J. Kim, "Ethical challenges regarding artificial intelligence in medicine from the perspective of scientific editing and peer review," *Sci. Ed.*, vol. 6, no. 2, pp. 91–98, 2019.
[108] S. H. Park, K.-H. Do, S. Kim, J. H. Park, and Y.-S. Lim, "What should medical students know about artificial intelligence in medicine?," *J. Educ. Eval. Health Prof.*, vol. 16, 2019.

Conflict of Interest

The authors declare that there is no conflict of interest regarding the publication of this article.