Online Medical Consultation Service-Oriented Recommendations: Systematic Review

Hongxun Jiang, ziyue Mi, wei xu

Submitted to: Journal of Medical Internet Research
on: March 10, 2023

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Hongxun Jiang[1*] PhD; ziyue Mi[1]; wei xu[1*] PhD

[1]Renmin University of China Beijing CN
[*]these authors contributed equally

Corresponding Author:
wei xu PhD
Renmin University of China
NO.59, ZHONGGUANCUN STREET
HAIDIAN
Beijing
CN

Abstract

Background: Online health communities (OHCs) have given rise to a new e-service known as online medical consultation (OMC), enabling remote interactions between physicians and patients. To address challenges such as patient information overload and uneven distribution of physician visits, OHCs should develop OMC-oriented recommenders.

Objective: We aimed to comprehensively investigate what paradigms lead to the success of OMC-oriented recommendations.

Methods: A literature search conducted through e-databases, including PubMed, ACM Digital Library, Springer, and ScienceDirect from January 2011 to December 2023. This review included all papers directly and indirectly related to the topic of healthcare-related recommendations for online services.

Results: The search identified 369 articles, of which 26 met the inclusion criteria. Despite the growing academic interest in OMC recommendations, there remains a lack of consensus of e-service-oriented recommenders on their definition among researchers. The discussion highlights three key factors influencing recommender success: features, algorithms, and metrics. It advocates for moving beyond traditional e-commerce-oriented recommenders to establish an innovative theoretical framework for e-service-oriented recommenders and addresses critical technical issues in two-sided personalized recommendations.

Conclusions: The review underscores the essence of e-services, particularly in knowledge-intensive and labor-intensive domains like OMC, where patients seek interpretable recommendations due to their lack of domain knowledge, and physicians must balance their energy levels to avoid overworking. Our study's findings shed light on the importance of customizing e-service-oriented personalized recommendations to meet the distinct expectations of two-sided users, considering their cognitive abilities, decision-making perspectives, and preferences. To achieve this, a paradigm shift is essential to develop unique attributes and explore distinct content tailored for both parties involved.

(JMIR Preprints 10/03/2023:46073)
DOI: https://doi.org/10.2196/preprints.46073

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Original Manuscript

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Hongxun JIANG, Ziyue MI, Wei XU*
School of Information, Renmin University of China

Corresponding Author:
Wei Xu, PhD, Professor
The department of Economic Information Management,
School of Information, Renmin University of China
No. 59, Zhongguancun Street, Haidian District
Beijing, 100872
China
Phone: 86 10 82500904
Fax: 86 10 62511184
Email: weixu@ruc.edu.cn

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Keywords

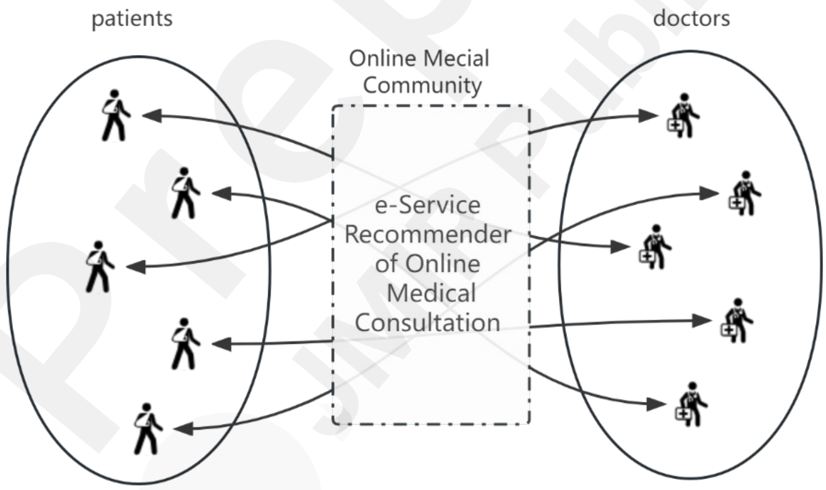
online health community; online medical consultation; personalized recommendations; two-sided matching; load balancing

Introduction

Technology innovations have brought the medical industry into the digital, networked, and intelligent era of the medical internet. Combined with the impact of the pandemic, telemedicine increasingly prevails. A growing number of patients start to seek contactless counseling from physicians through online health communities (OHCs). Meanwhile, physicians are providing the public with healthcare posts, free medical consultation and even paid customized service[1-3]. The *haodf.com*, one of the leading OHC platforms in China, till March 2023 has collected more than 890,000 physicians from 10,000 hospitals across the country. It offers patients the service of telehealth or online live chat, i.e., online medical consultation (OMC). Telehealth offers greater convenience to patients than in-person visits previously available. However, it deteriorates the problem of information overload, as there are too many candidates for users to choose from, which exacerbates the level of hesitation [4]. Patients face challenges in selecting suitable physicians due to limited medical knowledge and cognitive abilities. An OMC-oriented recommendation system is crucial to provide patients with professional, accurate, and responsible referrals, ensuring they connect with qualified and suitable physicians.

Most existing studies of physician recommendations are in the wrong direction, regardless of their diverse methodologies, such as collaborative filtering, demographic statistics, or association rules. The previous research overlooked the fact that OHCs serve both patients and physicians, i.e., a two-sided market scenario. Figure 1 illustrates an OHC jointly formed by patients and physicians. When a market is two-sided, there are cross-network externalities, which means that the number of users on one side will affect the number of users on the other side and the overall transaction volume on both sides [5]. An OMC recommendation is a service that an OHC offers both two sides of users. Such a kind of online service like OMC, namely e-service, is an emerging field of internet business under the knowledge economy. As opposed to e-commerce, the e-service is composed of consultees and consultants rather than users and commodities. The offered item is an intangible service rather than a tangible one but has to meet the different needs, expectations, and preferences of two-sided users. Further, medical consultations are knowledge-intensive and labor-intensive services that demand high levels of professionalism and energy investment [6]. The energy limits of physicians vary, and each physician can receive consultations only to a certain extent. In addition, patients lack the professional knowledge to distinguish the candidates, so they need recommendations that can be interpreted. So it is impossible to transplant an e-commerce recommending model to solve the OMC recommendation cases. Research in recommendation systems suffers from a ”blind side” that is the lack of research focusing on service-oriented applications, requiring academicians to develop new attributes and research new content. OMC service demonstrates the typical characteristics of online knowledge services, which represent the emerging trend of the “Internet+” economy. In the context of the knowledge economy, research on service recommendations is particularly pertinent, and now is an excellent time to start. As far as we know, no comprehensive research has been conducted in academic circles on service recommendations. Personalized service recommendation is a new topic yet to be clearly defined and fully explored.

Figure 1. OHCs function as two-sided markets involving both patients and physicians. In such markets, the user base on one side of the platform affects the user base on the other side, leading to cross-network externalities that influence the overall transaction volume across both sides. Recommendation systems must consider both patients' and physicians' needs and preferences.



Despite several reviews on healthcare recommender systems focusing on patient interests[7-9], there remains a gap in service-oriented recommendations. Our systematic review aims to fill this void by concentrating solely on two-sided recommendations. By providing the latest review in this domain, we aim to gather comprehensive evidence for evaluating current studies, identifying successful paradigms and approaches in service-oriented recommendations, and informing public health interventions and policy-making. This will leverage two-sided recommendation technologies to enhance the well-being of both patients and physicians in the emerging OMC service industry.

Methods

This review was conducted according to the PRISMA guidelines (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) (Multimedia Appendix 1) [10, 11].

Search strategy

Since the OMC service-oriented recommendation system spans multiple disciplines such as healthcare, business information systems, and computer science, the authors conducted separate literature searches in each field's databases. These included one medical-focused database, PubMed, one computer-focused database, ACM Digital Library, and two multidisciplinary full-text databases, SpringerLink and ScienceDirect, from two leading publishing groups, Springer and Elsevier, respectively. Our search was tailored to the review topic, followed by an analysis of text words found in titles, abstracts, and keywords used in retrieved papers. The electronic search was conducted in December 2023, utilizing keyword combinations in the Title/Abstract/Keywords fields to ensure comprehensive coverage. Keywords were selected and categorized into 4 categories: OMC (subject of the study), recomendation (objective of the study), OHC (fields of the study), and excluded keywords, namely query #1 to #4, respectively. To emphasize the recent advancements, an additional query #5 set a time limit of January 1, 2001, until November 1, 2023. The overall search strategy was #1 AND #2 AND #3 AND (NOT #4) AND #5. Table 1 presents the hierarchical search query and all keywords.

Table 1. Literature search strategy.

Search	keywords
#1 Title	(doctor OR physician OR consultation OR treatment OR e-health OR m-health OR telehealth OR remote health OR digital health OR online medical service OR web-based, health OR internet-based, health)
#2 Title	(recommendation OR recommender OR recommending OR matching OR rating OR choosing OR selection)
#3 Title/Abstract/Keywords	((Health OR Healthcare) AND (Communities OR Forums OR Platforms))
#4 Title/Abstract/Keywords	(Qualitative research OR Practice)
#5 Time range	January 1, 2011, to November 1, 2023

Following the keyword search, a reference list search (i.e., backward reference search) and a cited reference search (i.e., forward reference search) were conducted on the full-text articles that met the study selection criteria. Using the results of the backward and forward reference searches, the same study selection criteria were applied to further screen and evaluate articles. We repeated these procedures on all newly identified articles until no additional relevant articles were found.

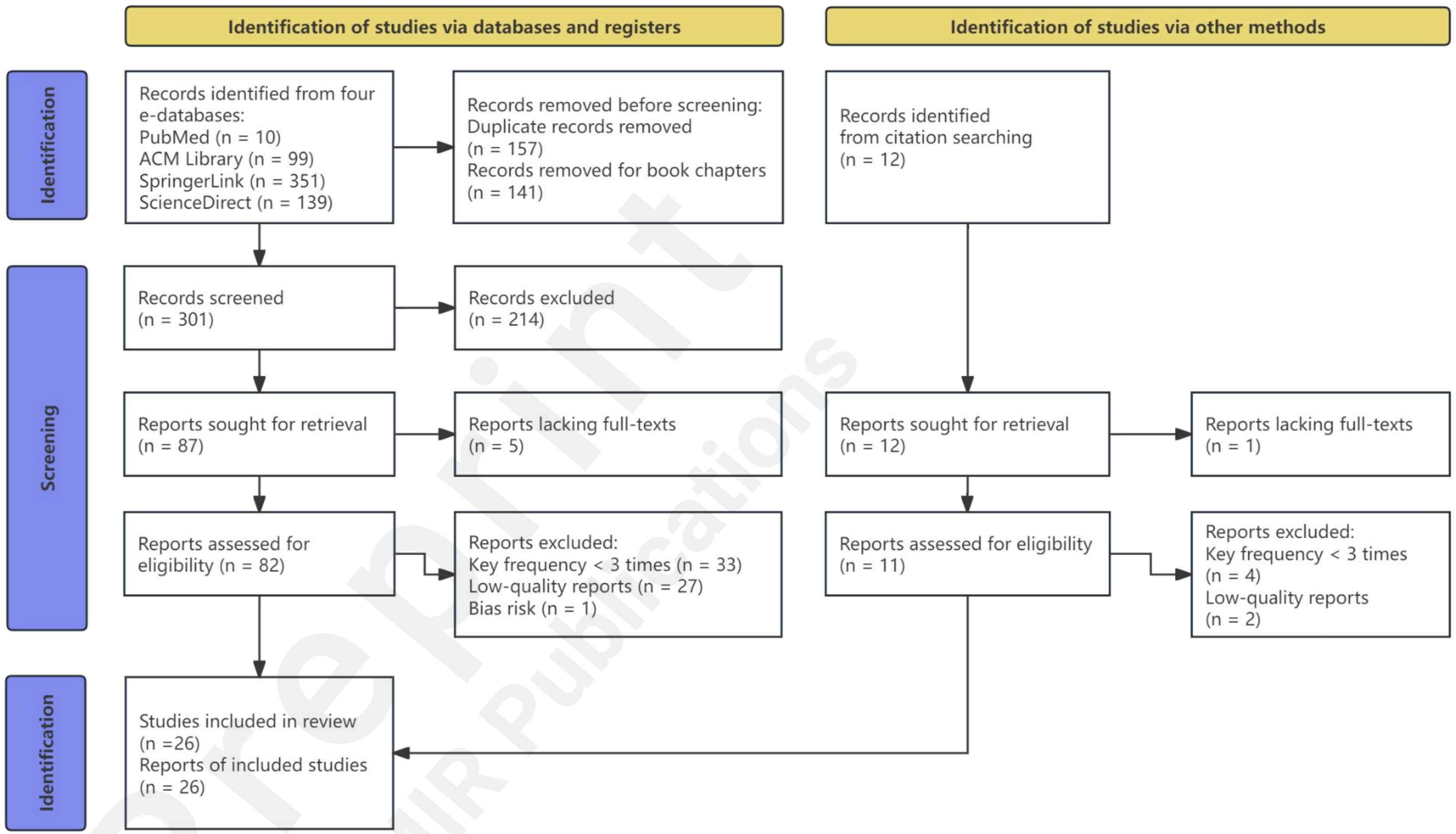
Eligibility criteria

The titles and abstracts of identified articles were independently screened by two researchers (HJ and ZM) to determine inclusion in the full review. Figure 2 illustrates the paper selection process. If either or both reviewers selected the paper for further evaluation, it was included for full assessment. Articles were considered for analysis if they met at least one of the following criteria: (1) OHC-oriented physician recommendations; (2) coding or documenting patient preferences; (3) motivations or perceptions of physicians involved in OHCs; (4) implementation of a recommender system for medical services; or (5) recommendation acceptance and interface design in the domain of medical-related recommender systems. Disagreements were resolved with a third reviewer (WX) until consensus was reached. Additionally, articles must have met the following three criteria to be considered for analysis: (1) published in peer-reviewed journals or conference proceedings, excluding research articles without detailed research designs or results; (2) written in English; and (3) published between 2011 and 2023 to align with the recent emergence of OHCs over the last decade.

Quality assessment

To ensure the quality of the articles, we applied a GRADE (Grading of Recommendations, Assessment, Development, and Evaluations) framework. The purpose of this initiative is to help individuals make informed decisions by using evidence systematically and transparently [12]. The GRADE Evidence to Decision (EtD) frameworks have been illustrated and are useful in making and using health-related recommendations and decisions [13]. It identifies four levels of evidence for each study: very low, low, moderate, and high. GRADE criteria examine the risk of bias, imprecision, inconsistency, indirectness, and publication bias in evaluating the quality or evidence of a study [14]. In the scenario of OMC recommendation design, those studies start at high quality or evidence if they use both offline datasets and online data streams for randomized controlled experiments. In contrast, observational studies begin with a lower quality or evidence due to residual confounding. Referring to previous studies [15], only moderate and high-quality articles were selected to avoid low-quality articles.

Figure 2. PRISMA (Preferred Reporting Items for Systematic Review and Meta-Analysis) diagram of the study.



Results

Search results

The electronic database search yielded 599 studies, with an additional 12 studies identified from Google Scholar through reference list and cited reference searches for each obtained study. After removing book chapters and deduplicating entries, 301 studies remained. The review process involved excluding 214 ineligible studies after screening titles and abstracts, as they did not meet the criteria for physician recommendations thematic-specific, OMC domain-specific, peer-reviewed source-specific, or English-specific requirements. This left 87 studies for full-text review. Five reports were found to have no full texts and were subsequently removed. The full texts of the remaining 82 studies were assessed for bias risks and qualitatively analyzed. Ultimately, 21 high-quality studies with adequate outcome data were selected for quantitative analysis. Additionally, five studies were identified through citation searching and included in the quantitative analysis.

Study characteristics

Table 2 summarizes the features and discoveries of each of the 26 studies. The number of publications increases over time. That indicates that this field is receiving more and more attention from scholars and practitioners due to the global prosperity of OHCs. This review consists of studies from six countries across Asia, Europe and North America, the majority of which are developing countries. The largest source of articles is China, followed by Portugal and India. That reflects that in countries with less developed offline health networks, online medical services are of particular benefit, as illustrated by the growth of OMCs in China. There were various recommendation algorithms used: analytic hierarchy process (AHP), collaborative filtering (CF), content-based filtering, decision tree (DT), neural network (NN), matrix factorization (MF) and regression analysis. Although research has been conducted using a variety of methods, but CF, MF and AHP are the top three most commonly used ones, with ten studies involving their use entirely or in part. Over the last five years, however, the research methods of graph-based deep learning have become increasingly popular. The most widely used method of data engineering in the field is text analysis, such as Latent dirichlet allocation (LDA) and word2vec, followed by knowledge graphs.

Table 2. The bibliographic and characteristics of the included studies

Author	Time	Country	Study aim	Method	Data sources
Huang et al. [16]	2012,12	China	Using patient preferences and doctor performance to recommend doctors	Collaborative filtering (CF), Analytic hierarchy process (AHP)	Official appointment platform for Shanghai

					Medical League
Jiang et al. [17]	2014,12	China	Combining the relevance and quality of doctors in an integrated recommender	semantic similarity computing, AHP	OHCs: Haodf, xywy, ask39, 51daifu
Gong et al. [18]	2015,9	China	Using medical social networks and a medical dataset to recommend doctors	Time-constraint probability factor graph, random walk with restart	Clinic experiments at Chinese Academy of Sciences
Narducci et al. [19]	2015,5	Italy	Delivering a semantic recommender system based on social networks	Similarity computing, CF	N/A
Guo et al. [20]	2016,7	China	Identifying KOLs with health care data mining for any specific disease	Unsupervised aggregation approach,	Medical journal papers
Zhang et al. [21]	2017,1	China/ USA	Using topic model and emotional offset to recommend doctors	Matrix factorization, LDA, sentiment analysis	Yelp
Sridevi et al. [22]	2018,8	India	A personalized doctor recommender	Similarity computation, combined ratings	N/A
Han et al. [23]	2018.10	Portugal	Establishing a mechanism for matching patients with family doctors	hybrid matrix factorization, latent representation	Consultation histories of a leading European healthcare provider
Waqar et al. [24]	2019,1	Pakistan	Combining content base, collaborative and demographic filtering to create a hybrid doctor-recommender	Content-based filtering, CF, Similarity measure, AHP	Survey data from three hospitals in Isla-mabad, Pakistan
Pan et al. [25]	2019,1	China	Personalizing physician selections based on patient preferences and illness conditions	Dynamic assortment planning, upper confidence bound	Simulation data
Xu et al. [26]	2019, 6	China	Recommendations based on doctors' reputation scores and similarities with patients' demands	Truth discovery, modified paillier cryptosystem, Dirichlet distribution	Simulation data

Yan et al. [27]	2019,8	China	Picking up doctors using signaling theory with patient needs	Binary long short-term memory, LDA, regression, AHP	OHCs: Haodf, xywy
Yang et al. [28]	2020,2	China	Enhancing doctor recommendations based on patient preferences	Intuitionistic fuzzy sets, Bonferroni mean	OHC: Haodf
Wen et al. [29]	2020,4	China	Providing real-time personalized recommendations by optimizing limited physician resources	Adjust-exponential inventory balancing	Simulation data
Mondal et al. [30]	2020,10	India	Modeling patient-doctor relationships to recommend doctors	Multilayer graph data model	Records from health centers and hospitals
Yan et al. [31]	2020,10	China	Fusing review text and doctor information to improve medical consultation recommendations	Convolutional neural network, Probabilistic matrix factorization	OHC: Haodf
Meng et al. [32]	2021,1	China	To propose a hybrid doctor recommendation model based on OHC	Eigenvector, word2vec, latent Dirichlet allocation	OHC: Chunyu
Peito et al. [33]	2021,1	Portugal	Developing a content-based matchmaking system for patients and doctors	Pre-trained Poincaré embeddings, transfer learning	A dataset of an European private health network
Wang et al. [34]	2021,1	China	Proposing a diversity-enhanced hierarchical physician recommendation approach	matrix factorization, heuristics	OHC: Haodf
Ju et al. [35]	2021,8	China	Ontology-based recommendation of doctors based on disease text mining	Ontology, text mining	OHCs: Guahao
Yuan et al. [4]	2022, 2	China	Using knowledge graphs and deep learning to recommend doctors based on OHCs	Knowledge graph, deep learning	OHC: Haodf
Lu et al. [36]	2022, 5	China	recommending doctors through expertise learning in OHCs	Multi-head attention, pre-trained BERT	OHC: Chunyu
Chen et al. [37]	2022, 7	China	Considering patient's risk preference in a probabilistic linguistic environment to recommend doctors	probabilistic linguistic term set, TF-IDF, Word2Vec	OHC: Haodf
Wang et al.	2022,8	China	Developing a model to	Lasso, multilayer	OHC: Haodf

[38]			predict patients' preferences in medical consultations based on physician characteristics	perceptron, decision Tree, Shapley Additive exPlanations	
Wu et al. [39]	2023, 2	China	Making a decision-making method for online doctor selection that considers correlation	Choquet integral, BERT, 2-additive fuzzy measure	OHC: Dxy
Valdeira et al. [40]	2023,8	Portugal	Doctor recommendation with implicit feedback and limited patient information	Deep extreme classification with label features	Consultations of an European private health network

Of the 26 studies included, 13 used data directly from OHCs as their data sources, while the remaining seven used data indirectly from the official websites of hospitals or healthcare centers. Depending on the sources, the data sets can be classified as online or offline. There are numerous OHCs, which produce massive amounts of heterogeneous, multi-modal, and high-dimensional raw data continuously [41, 42]. Online Data generated by these OHCs supports medical diagnosis and decision-making. Offline data is usually collected from various medical institutions and typically stored in healthcare information systems. They will be exported once permission has been granted [16, 18, 23, 30, 40]. In addition, many studies collect primary data through questionnaires directed at patients or physicians [24]. Depending on the objects described, the data sets can be classified as patient, physician, and institution data, as shown in Table 3. The data quality of physician profiles, such as educational background, professional experience, disciplines, expertise, etc., is high and well-defined. The patients are OHC users and service consumers, but they are ignoramuses in the medical field, who usually chat online without any restrictions or limitations, which results in poor-quality data from their consultations. This makes data processing and feature extraction quite complicated and challenging.

Table 3. The OHCs' dataset contains various categories and features, including information related to physicians, patients, and hospitals.

Categories	Features	Description
Physician profiles	ID, name, age, gender, geographic location, hospital, department	doctor's personal information
	Specialties, number of patients, professional title	professional experience and expertise
	Academic background, research achievements, academic titles	academic background
	Patient ratings, patient reviews, patient satisfaction	online/offline Word of Mouth
	Number of popular science articles	
	Historical records	physicians' historical consultations
Patient profiles	ID, gender, age, location	patients' personal basic information

	Disease description and medical history	disease information provided by the patient in advance
	Consulting records	records of patient consultations with physicians
Hospital information	Hospital grade and ranking	hospital reputation

Data and feature engineering

An accurate acquisition of features enables an effective recommendation system, and feature engineering forms the foundation of personalized recommendation systems. Data engineering begins with raw data preprocessing. Duplicate or missing values can be handled by deleting them or using average values. Semi-structured data, such as the demographics of physicians or patients, needs to be converted into structured data by recognizing named entities and extracting information. When analyzing unstructured data, such as physician-patient consultation records, the content may be nonstandard, repetitive, short, and straightforward. Pycorrector, a third-party open-source library developed by Python, can be used to correct some common errors in oral expression[35]. Afterward, word separation, deactivation removal, normalization, and other procedures will be performed. A word separation process extracts and vectorizes text features. Considering the specificity and professional nature of the medical field, the consultation records contain many medical professional words, and synonymous disease names must be substituted, e.g., the term “trisomy 21” indicates a pediatric Down’s syndrome disorder. To ensure that professional terms are recognized during word segmentation, it is recommended to develop a dictionary based on medical ontologies. Furthermore, medical experts can be consulted to refine the dictionary by deleting terms outside the required domain[4]. Afterward, stopwords should be removed to eliminate meaningless words or characters and to reduce noise. For word segmentation, the most commonly used tools are Jieba and Word-Net Lemmatizer in the NLTK library; for removing stopwords, the most commonly used lexicons include HIT stopwords list, Baidu stopwords list, stopwords in the NLTK library, etc.

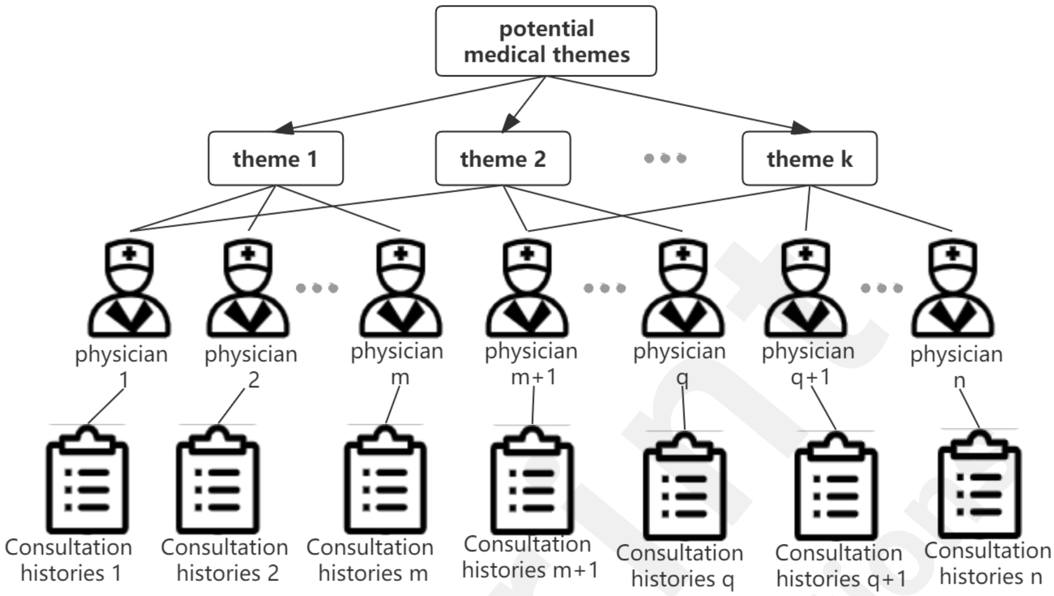
OMC recommendations also face data sparsity challenges. Domain specialization leads to data sparsity. An OMC is not one of fast-moving consumer goods but a professional service. Most people do not consult physicians regularly, but rather initiate consultations only when they need one, such as when a condition arises. In most cases, patients will consult only one physician for a condition or disease. Once cured, they will not revisit the same physician; Otherwise, they will try another physician. In other words, it is rare for a physician and patient to have multiple records of the same condition or disease. Despite OHCs having an extensive collection of physicians, most of those physicians are considered to be “silent” in the communities, since in most cases patients pay attention only to those physicians who are well-known and highly regarded. It was only possible for patients to rate or write reviews for physicians they had consulted rather than for other physicians. All these factors contribute to data sparsity.

To alleviate data sparsity, either improve the model or mine more features. According to the literature [26], patients' uncertain characteristics and preferences could be revealed by uncertainty languages, and fuzzy analysis could be used to improve recommender systems' sparsity problem. Knowledge graphs had been introduced to represent physician-patient interaction features in the physician recommendation problem, thereby alleviating data sparsity [4]. A socio-semantic approach was utilized to address the problem of data sparsity caused by user-based collaborative filtering [43]. Son and Choi used ordinal and binary ratings of experts to refine user opinions and mitigated data sparsity in hand-edited expert recommendations [44]. Wang et al proposed a matrix decomposition to handle sparse data and improve prediction accuracy [34].

Medicine is a very specialized field of science. Often, because of cognitive limitations, patients cannot express their conditions and medical histories in consultation content, and some are unable to even express their personal needs. Using topic models, unstructured texts are analyzed for their content to retrieve, classify, cluster, summarise, and find topics that have similarities or relevance. The most common topic modeling method, LDA, utilizes an unsupervised probabilistic model to generate topics [27]. Typically, LDA is used to extract topics from large data sets of documents by mining potential semantic relationships between them. Meng et al used all physician consultations as a corpus for LDA, as shown in Figure 3, and each physician receiving text-topic distribution was trained to retrieve the corresponding physician within a specific topic [32]. Zhang et al applied LDA to extract patients' potential preferences and the characteristics of the physicians they consulted from patient reviews [21]. LDA has some shortcomings. First, LDA lacks semantic contextual information when processing text, because the commonly used Bag of Words (BoW) model ignores it [31]. Secondly, LDA models perform poorly when text topics are too sparse to represent potential features; training LDAs tends to overfit if there are too many topics, so a fair number of topics must be selected to strike a balance between the degree of fit and simplicity. Last but not least, LDA models cannot handle labeled data on documents, causing uninterpretable topics to be generated. From various perspectives, scholars have proposed solutions to the above-mentioned drawbacks. Ye et al reduced the time complexity of LDA via Gibbs sampling and determined the optimal number of LDA topics based on the confusion level [27]. Because the patient's "initial inquiry" text is usually short and the corresponding topic vector representation is sparse, Liu used a short text aggregation algorithm to represent the topic vector [45]. Pan and Ni used a Labeled-LDA model to generate probability distributions for health questions/topics and topics/words based on the text set of physicians' answers to health questions [46].

Figure 3. Identifying each physician's specialty involved analyzing their historical consultation texts

using medical terminology recognition and topic classification mining.



Sentiment analysis identifies users' attitudes and opinions on commodities or services from their review texts. Besides medical topics, consultations and patient evaluations at OHC include patient emotions and feelings as well. Using sentiment mining techniques, sentiment information can be extracted from text data. Text sentiment analysis can be divided into two main types: lexicon-based and deep learning-based. Sentiment dictionaries are the traditional tool for analyzing words and short texts' sentiment tendencies [27]. These dictionaries describe not only the positive and negative sentiment attributes of words in static dictionaries but also the offsets of sentiment information of words in sentence frameworks. China national knowledge infrastructure (CNKI), the information retrieval laboratory at Dalian University of Technology (DUTIR), and the natural language processing and social humanities computing laboratory at Tsinghua university (THUNLP) are three dictionaries commonly used for sentiment analysis of Chinese texts. Based on sentiment dictionaries, Zhang et al. used unsupervised learning methods to calculate the offset between patients' comments and their sentiments and correct the original patient ratings [21]. There is evidence that deep learning is superior in the analysis of long texts containing complex sentiments. To analyze positive and negative sentiments in patient reviews, Ye et al utilized the binary long-term short-term memory (Bi-LSTM) method, which achieved better results than sentiment dictionary analysis[27]. For sentiment polarity analysis in review texts, Wu and Sun used the BERT model, and for recommendation results, they applied the Wilson interval method [47]. Due to the subjective nature of patient comments and the unreliability of sentiment ratings, sentiment mining methods have limitations. Data sources of uneven quality can also affect the accuracy of sentiment evaluations. The fuzzy analysis of the text can help address the uncertainty of text description [48]. The fuzzy analysis mainly applies fuzzy mathematical or fuzzy linguistic methods, which allow recommender systems to express uncertainty and obtain personalized features from patient comments. Intuitionistic fuzzy numbers (IFNs) serve as effective tools for dealing with fuzzy information, i.e., describing the degree of neutrality in uncertain situations [49]. Yang et al. converted raw data into IFNs to describe uncertainty information by combining the patient's disease description with comments [28]. Xu et al examined data based on hesitant fuzzy language multi-criteria preference analysis to enhance patient preferences for physician recommendations [48].

Recommendation algorithms

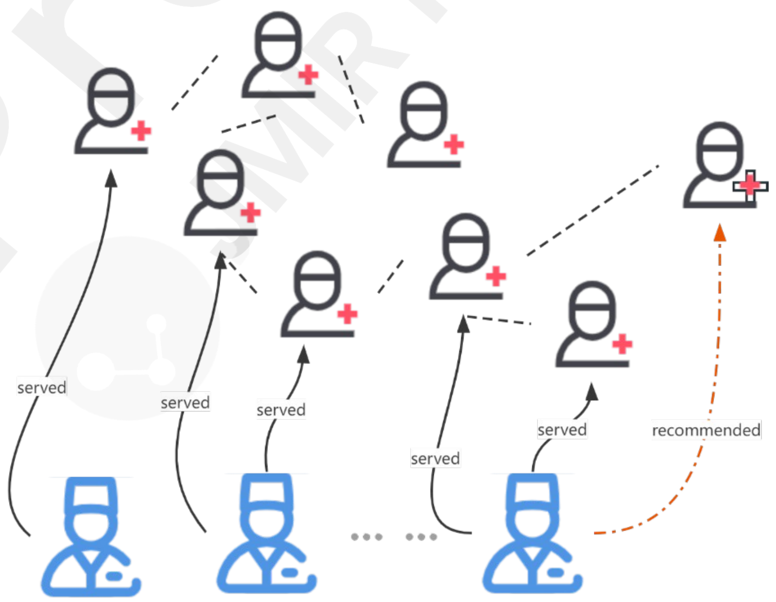
The OMC recommendation is recommending a service with suitable physicians according to the patient's needs, an application scenario differing from the application scenario of item recommendation in e-commerce, rather resembling expert discovery in online Q&A communities or academic peer review. These recommendations have one thing in common: the recommended subject is not a product, but rather a human, a competent and knowledgeable professional. A physician's expertise can be inferred from his or her educational and professional background, as well as historical consultations, similar to the history of expert responses in Q&A communities or the list of academic papers. Patient comments and ratings for a physician are similar to the number of likes for a Q&A expert or citations of a scholar. It can be compared to assigning a competent academic reviewer to a new topic, finding a suitable expert to answer a new question, or recommending an appropriate physician based on graphic descriptions of the patient's consultation.

(a) Knowledge-oriented recommendations

Knowledge-intensive service recommendations are determined by matching large amounts of textual information between patients' inquiries and physicians' skill sets. In general, the better the information match, the more likely the service recommendation will be successful. As part of content-based recommendations, physicians' backgrounds and historical data are gathered, and textual topic techniques are used to mine their expertise, such as Latent Dirichlet Allocation (LDA), probabilistic Latent Semantic Analysis (pLSA), and so forth. Pan and Ni modeled the textual topics of historical consultations and physician responses under each section [46], mined physician expertise using Labeled-LDA, and completed physician recommendations based on candidate physician expertise and pending inquiries.

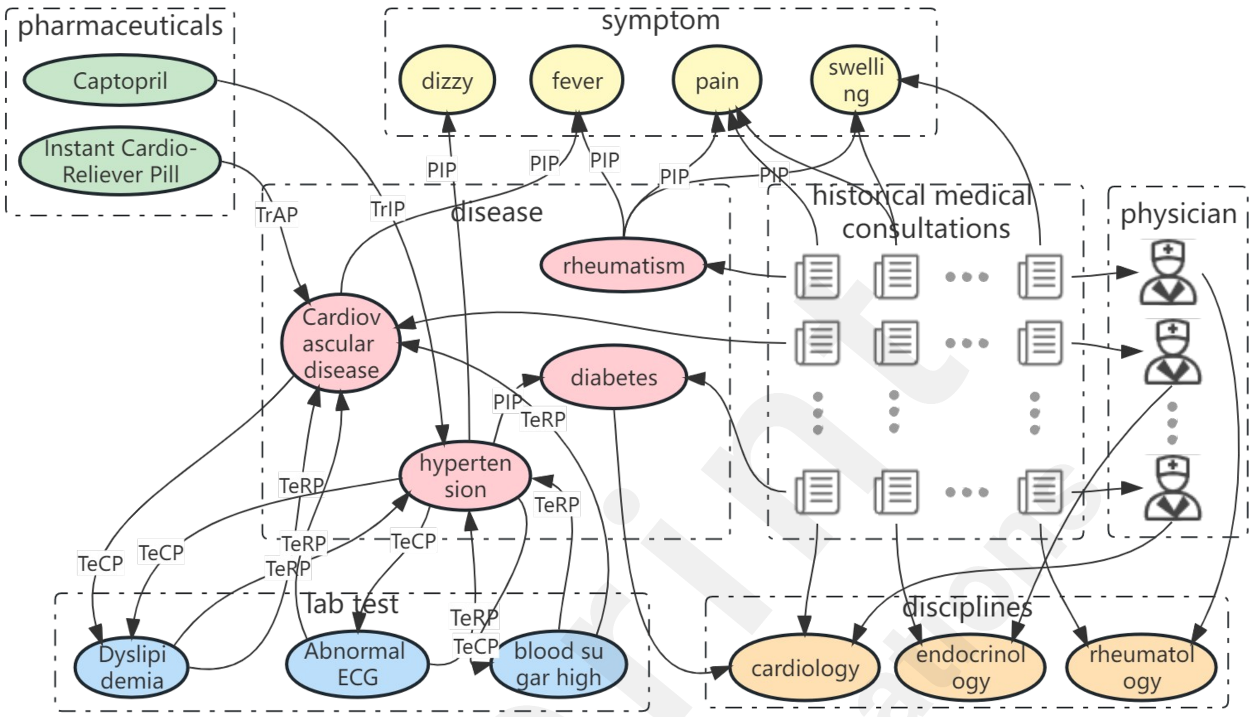
Social network-based expert recommendations have grown in popularity, which derives from a classical algorithm of information retrieval, i.e., PageRank. For expert recommendations, Wang et al proposed a convolutional neural network for answering online expert questions [50], which effectively reduces waiting time for the questioner and improves the quality of the answer. To alleviate the cold start problem for new-coming patients, physician recommendation-related studies should consider patients with similar conditions in the OHC, who exchange information and provide emotional support, as illustrated in Figure 4. Recently, expert recommendation research has increasingly incorporated integrated models that combine features such as social networks and knowledge content. Xu et al proposed a scholarly recommendation framework that integrates social network analysis and conceptual semantic analysis in two dimensions: social relationships among scholars and information about their expertise [51]. Yang et al employed information about research relevance, personal social networks, and institutional connections to identify the most appropriate experts for collaboration on research [52]. Xu et al proposed a methodology for a collaborative recommendation that integrates expert expertise and social information in a complex heterogeneous network utilizing heterogeneous network mining [53]. It identifies valuable meta-paths through information gain, and it uses regularized optimization to generate personalized recommendations tailored to each scholar's needs. Different recommendation algorithms have different strengths in comparison. Expert recommendations based on knowledge content are better suited for use in enterprises with high levels of information quality and clearly defined knowledge hierarchies. Information quality in OHCs is significantly lower than that in general organizations, and expert recommendations are greatly influenced by the structure of social networks [54]. Both of these features are present in the OMC service recommendations studied in this study.

Figure 4. Social network-based recommendations leverage patient-friend relationships to recommend a doctor to a new patient with a similar condition, aiming to gain the trust of the new patient.



A knowledge Graph (KG) is a structured semantic knowledge base that integrates heterogeneous information from multiple sources and represents rich entity relationships using complex networks, which facilitates the storage, processing, and communication of complex real-world knowledge. Medicine is a specialized scientific field, and vector representations of knowledge graphs enable algorithms to obtain embeddings of concepts, class hierarchies, entities, and relationships, and in turn, graph structures, paths, and subgraphs. Algorithms can achieve logical reasoning in vector space with the help of ontology embedding and rule learning. For the OHC platform to be credible, physicians must provide their real names, educational backgrounds, professional experience, and expertise, so that their profiles can be verified. Using document clustering analysis, LDA topic segmentation, and feature extraction from physician historical consultations, a knowledge graph describing physician specialty and expertise can be constructed. Yuan and Deng produced a more accurate and interpretable recommendation scheme based on the knowledge graph to overcome the problem of sparse data [4]. It is common practice for existing studies to extract entities based on physician historical consultations, however, these data alone are not sufficient to represent physician professional specialties. For example, if an otolaryngologist has only received consultations related to the ear and nose for various reasons, then the system only measures his or her expertise in the ear and nose. However, in practice, he or she also has excellent expertise in laryngology, which the system cannot calculate. An appropriate recommendation system should be designed to recognize the differences between specific diseases and the expertise of various physicians within the same department. As shown in Figure 5, the original scope of historical consultations should be extended to include new entity nodes such as specialized disciplines, physicians, and consultations. To optimize the network structure of the knowledge graph, we should analyze the semantic connotation of keywords, determine the semantic similarity between consulting cases and their attribution to specialized disciplines, and examine the professional areas of physicians and their evolution trends.

Figure 5. Constructing a physicians' knowledge graph: an example in cardiovascular medicine. The knowledge graph comprises various medical entity nodes, such as specialized disciplines, diseases, symptoms, and pharmaceuticals. These entities are extracted from the historical consultation records of physicians.



Knowledge graph-based physician recommendations are a new trend in OMC service recommendations. By using logistic regression, plain Bayesian classification, and noise-gate Bayesian networks, Rotmensch et al constructed a knowledge graph, and from the parameter training, a disease-symptom topological relationship graph was generated [55]. Liu used the K-means algorithm to cluster physicians and generalized goodness-of-fit metrics to evaluate and adjust the clustering results [45]. By comparing the patient's consultation content with the physician clustering center and the individual physician information in each category, a physician category and physician object that is more closely matched could be recommended. Xu et al proposed a collaborative recommendation method for scholars based on heterogeneous network mining, combining expert expertise with social information, identifying valuable metapaths through information gain, and providing personalized recommendations for each scholar through canonical optimization [53]. Based on the similarity of consultation texts, Xiong and Meng constructed a co-occurrence label network of physicians and calculated the centrality of the feature vector to recommend the most important physicians [32]. Gong et al proposed a hybrid multi-layer architecture iBole of physician recommendations, mining physician-patient relationships with a time-constrained probabilistic factor graph model, and recommending physicians based on random wandering [18]. KG-based physician recommendations also have drawbacks. The OMC service faces more complicated application scenarios involving multiple entities and inter-entity relationships that reflect a physician's knowledge or disease symptom connection. It is difficult to integrate different attributes and relationships between attributes in traditional recommendation methods, and it is nearly impossible to visualize the relationship between each knowledge attribute and physicians. KG-based OMC service recommendations should utilize multi-source heterogeneous information to mine physicians' comprehensive expertise, take their profiles as basic professional descriptions, mine all their published articles using text semantics, and then combine their historical consultations with multimodal data to extract features using multimodal mining and LDA topic segmentation.

(b) Interpretable recommendations

As medicine is such a specialized field of science, recommendations must be interpreted according to the patient's cognitive capacity. It is difficult for patients to make autonomous judgments about the recommendations with their knowledge because they lack theories and relevant experience. Most of the existing research on recommendation systems is devoted to the professional accuracy of recommendation results. They casually ignore the interpretability of recommendation schemes and the lack of transparency in the system computation process [4]. In other words, the recommendation process and logic are not adequately explained to patients by taking care of their cognitive capabilities. It is very critical for the recommendation system to be interpretable, as it directly correlates with the level of trust of patients [56]. To provide patients with a reference for decision-making, we believe that a good recommendation system for OMC services must incorporate an interpretable and user-friendly recommendation algorithm. As a result, patient acceptance and recognition of the recommendation results will be enhanced, which will ultimately result in a higher acceptance rate of the recommended solution of the system. As a result of their limited cognitive abilities, many patients, in addition to not judging the recommendations, struggle to make their inquiries clear and complete, and in a few cases, even cannot accurately articulate their personal needs. As an alternative to solving such difficult problems, multimodal data mining techniques may be considered, such as multimodal graphical topic modeling for patient description and consultation needs. Not only can key information from patient consultations be explored and labels extracted, but it is also possible to avoid creating too sparse input text variables by avoiding personalized verbal expressions and symptoms. Machine learning algorithms can easily process clustered documents when they are converted into vector distributions.

Recommendation algorithms can be interpreted in light of the rich semantic connections between physicians and patients in the knowledge graph [4]. Some studies have demonstrated that interpretable recommendation algorithms based on knowledge graphs enhance the level of patient trust. Using knowledge graph-based disease diagnosis algorithms, Wu and Sun obtained initial disease alternative sets by querying the knowledge graph and utilizing the knowledge graph embedding model, the knowledge graph-structured information was utilized to enrich the disease alternative set, enhancing the recommendation accuracy and facilitating the recommendation of potential diseases for the user [47]. To identify the different roles of physician-patient interaction characteristics and individual physician characteristics in physician recommendations, Yuan and Deng developed a deep learning model that can provide accurate and interpretable physician recommendation information by combining layer-by-layer association propagation techniques with deep neural networks [4]. Considering the accuracy, diversity, and interpretability of knowledge graph-based recommendations resulting from information such as rich semantic relationships and item links within a network, we propose that interpretable recommendations should be built based on knowledge graph path inferences. The algorithm should adopt a knowledge-aware path recurrent network (KPRN) model, which generates path representations by combining the semantics of entities and relations; reasoning by using sequential dependency in paths to infer interaction between users and items; incorporating a weighted pool into the process of inferring user preferences to differentiate between different contributions from different paths to provide interpretable recommendations.

Evaluation

Physician recommendations can be evaluated online or offline. Online evaluation involves measuring the effectiveness of the recommendation system by obtaining the target users' evaluation of the recommended object, namely, the rating of the recommended physician by patients. Guo et al asked three faculty members and three graduate students with medical backgrounds to judge candidate physicians based on their perception of their professional activities and reputation and to use the mean of the ratings to rank them [20]. Ye et al recruited 18 students with experience in helping relatives choose a physician to consult online, and asked them to assess the relevance of the physician in response to a given consultation question [27]. Wu and Sun used a questionnaire to assess the accuracy of a physician's recommendation and validate the proposed recommendation algorithm [47], including whether the respondents have suffered from a particular disease, have been treated in the area, and have approved the physician. An online evaluation has several shortcomings, including a high implementation cost and the difficulty of excluding the characteristics of the group surveyed as well as personal subjective factors from the results. An offline evaluation involves feeding training set data into the system for training the recommendation model and calculating the recommendation results based on test data to measure the performance of the recommendation system. In most cases, machine learning models are trained by supervised learning, which means the predicted output of the recommendation model is compared with the true value and based on the difference, model training methods can be altered and parameters can be adjusted to facilitate continuous optimization of the model [54]. There are different measurement criteria for measuring the difference between the predicted output of the model and the true value. Offline evaluations are predominantly based on accuracy, which includes classification accuracy, prediction accuracy, and ranking accuracy.

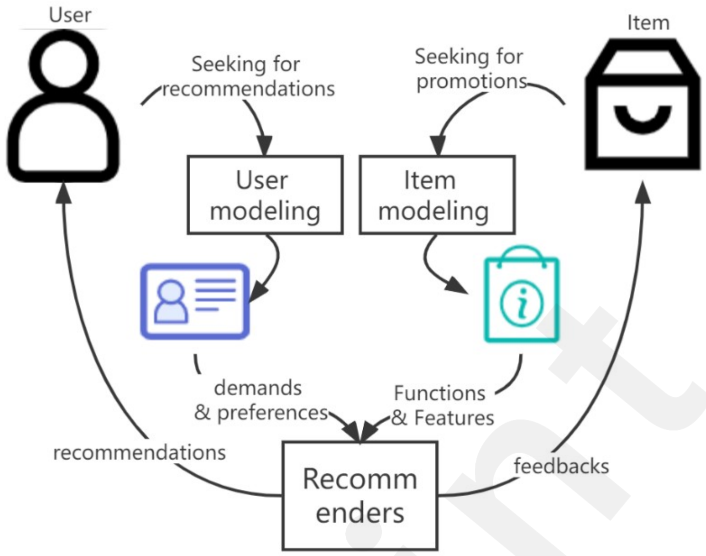
The diversity and coverage of recommended physicians have also been used to evaluate the performance of recommendation algorithms. According to the literature [28], recommending only similar physicians results in a limited choice for patients and an imbalance in physician utilization. Patients will be more likely to engage with the recommender system if there is more diversity of recommended physicians. A measure of coverage refers to the proportion of recommended physicians to all physicians [57]. A low level of coverage indicates that a limited number of physicians are available to patients. Patients are likely to be less satisfied with a recommender system if the candidate pool is limited. However, diversity and coverage metrics are not currently heavily utilized for evaluating physician recommendation systems. Physician recommendations differ from traditional e-commerce recommendations in some respects. Patients should be recommended physicians with similar expertise or experience that match their disease conditions, rather than a greater variety and number of physicians. Increasing the diversity and coverage of physician recommendations is unfavorable to patient outcomes, thereby affecting the application of these two metrics in physician recommendations.

Discussion

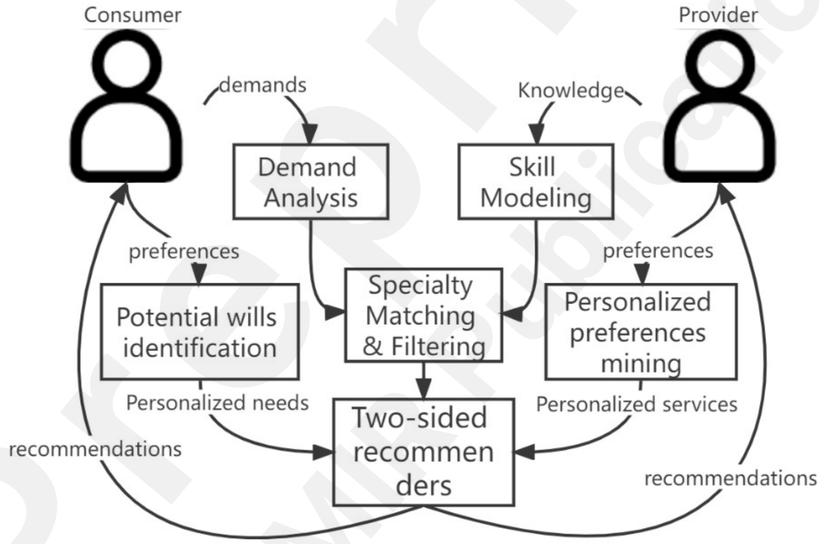
Principal Findings

Personalized recommendation studies previously focused on commodity recommendations based on “Users versus Items” and rarely considered service recommendations based on “Users versus Users”. This paper focuses on human carriers who deliver OMC services, particularly when recommending professional services. The OMC service represents a new form of e-business under the knowledge economy, as well as a new direction for the development of e-services. Figure 6 shows that a knowledge service-oriented recommendation differs from a traditional commodity-oriented recommendation from a system thinking perspective.

Figure 6. The distinction between commerce-oriented and service-oriented recommendations.Commerce-oriented recommendations focus solely on user preferences, disregarding item recommendation limits, while service-oriented recommendations must consider the needs and preferences of both parties involved, as well as the provider's capacity constraints.



(a) E-commerce oriented personalized recommendation system



(b) E-service oriented personalized recommendation system

An independent service-oriented recommendation system requires a novel theoretical framework and its key techniques. Table 4 illustrates the comparison between e-commerce and e-service recommendations. First, earlier studies only considered the interests and preferences of the user, not the feelings of the items recommended; the adoption of an OMC recommendation depends not only on the opinion of the consumer but also on the preference of the service provider. It is impossible to achieve even the so-called “best” recommendation scheme by focusing only on the needs of consumers but ignoring the individual preferences of service providers. And more, as the physician is more aware than the patient, he should have a higher priority in terms of decision-making [58]. Existing personalized recommendation systems have obvious flaws and weaknesses, both theoretically and algorithmically, even when designed specifically for consulting services. Although the recommended subjects in some expert recommendation system research, such as thesis review, project approval, and other scenarios, are also humans, the recommendation algorithm still focuses on the personalized characteristics of the demand side, analyzing only the professional skills of the experts rather than considering their preferences. These experts are just “tool men”. In the case of e-service recommendation applications like OMCs, such a research perspective and research conclusions are not applicable. Due to the existence of intrinsic and extrinsic needs of two-sided users, it is apparent that a new paradigm of personalized recommendation research must be based on a service-oriented approach.

Table 4. Comparision of commodities-oriented v.s. services-oriented personalized recommendations

	e-commerce oriented	e-service oriented
components	users v.s. commodities	users vs. users
recommended items	commodities	services
decision-makers	only users	two-sided users
personal preferences	only users	both patients and physicians
workload	N/A	physicians
reviews/ratings	important features	useful but needs caution
interpretability	optional	required

The professional characteristics of the service require that the system must provide consumers with explainable recommendations according to their cognitive levels. Medical diagnosis and treatment is a very specialized field. Most patients do not have a very clear understanding of this field. The model should be capable of explaining the recommendation schemes so that patients can make informed decisions[4]. In the case of e-commerce-oriented recommendations, interpretability is not required since users understand the utility of the items and what they desire. So the system simply needs to fully exploit the hidden needs and interests of users. Algorithms focus primarily on collecting users’ side information to identify their potential needs and respond to their individualized preferences [59]. Due to the consideration of medical privacy in the OMC scenario, the system is unable to extract patients’ hidden medical histories or other information from their historical treatment records[26]. Furthermore, patients generally lack medical knowledge and are unable to make independent judgments about the recommended results. Having interpretable algorithms improves not only the transparency of the recommendations but also the trust and acceptance of patients, which improves post-event satisfaction with physicians[4].

OMC’s particularity is also reflected in its knowledge-intensive and labor-intensive nature. OMCs are professional consultations and brain-consuming services that involve bilateral interactions between physicians and patients [60], so physician workload must be carefully considered. Traditional e-commerce-oriented recommendation algorithms typically produce “popular products” or “superstars”, which do not consider the overwork of physicians. In reality, it is impossible to achieve an overloaded recommended scheme, regardless of how well the patient’s condition matches the physician’s specialty. A few studies have addressed the “diversity” or “coverage” of recommendations, however, they only increase the total number of item types without considering the frequency of recommendations for a single item. Whenever a human-based service recommendation system is employed, the workload problem must be considered, yet it has rarely been taken into account in previous studies.

Data about users is not always valuable. Whether user reviews contribute to the formulation of recommendations is also a difference between OMC scenarios and those of other applications. Several previous studies have attempted to obtain useful information from patient reviews, but these efforts have proven unsuccessful [61, 62]. In general, patients are attracted to “popular” physicians with many positive reviews and few moderate and poor reviews, whereas young or unknown physicians are underrepresented, with few respondents and a lack of adequate review data. Three factors contribute to this phenomenon: patients are unprofessional, physicians are uncooperative, and evaluation of services is difficult. The first challenge is that patients are incapable of evaluating the effectiveness of professional services, and no significant correlation has been found between the online reviews of patients and their clinical outcomes [3]. Secondly, physicians will vigorously resist unprofessional, emotional, and malicious reviews that can harm their professional reputation [63], and may even “vote with their feet” to force the platform to block complaints. Thirdly, the success of OMC services is dependent not only on physicians’ professionalism but also on patients’ perceptions and expectations. In addition, it is still dependent on the collaborating medical examination or health care providers. Even the ease of use, stability, and privacy security of OHC platforms may have an impact on patients’ evaluations [64]. Until it has been established what techniques and methods are being used to extract key elements from subjective, ambiguous, and complex patient reviews, e-service-oriented personalized recommendation systems should be cautious about using comments and ratings.

Two-sided preferences

Personalized recommendations are based on user preferences, and acquiring accurate user preferences is key to ensuring their quality [25, 28]. In contrast to other recommendations, OMC recommendations need to consider both the preferences of consumers and providers, since an OHC is a two-sided market constituted by both patients and physicians, each with independent and stable preferences. Physician preferences have regrettably been ignored in previous recommendation systems, which resulted in infeasible recommendations. As a commercially complex adaptive system with differential and evolving goals, preferences, and constraints for both sides of a two-sided market, Malgonde et al proposed a two-sided recommendation framework for digital platforms to mitigate user emergence [5]. The patient’s personal preferences influence their selection behavior and thus their satisfaction with the recommendations[24, 29, 35]. In turn, the physician’s preferences influence his or her willingness to receive consultations, and in turn, the physician's onboarding and retention determine the continuity and development of the OHC [66]. Due to the differences in scale and quality of data between the two types of subjects, patients and physicians should have independent approaches to the extraction of features and the mining of behavioral patterns.

(a) Patient preferences

Patients' preferences and needs have been relatively adequately explored in existing studies on physician recommendations. As shown in Table 5, when choosing a physician, patients typically consider the physician's disciplinary background, professional competence, and institutional reputation, as well as other factors such as distance, cost, and follow-up care. To provide patients with personalized recommendations, Pan et al proposed a user preference learning algorithm to learn patient preferences [25]. Jiang and Xu proposed an integrated recommendation method that utilizes hierarchical analysis to screen candidate physicians based on three dimensions: semantic matching of physician-patient professional texts, objective evaluation of physician authority, and subjective evaluation of physician online word-of-mouth, respectively [17]. Ye et al employed SPSS to screen patient decision factors and recommend physicians based on their composite scores [67]. Wang et al even directly used the number of visits as an important determining factor for how patients viewed the standard of care provided by physicians [34]. Xu et al investigated the privacy issues of patients and provided a multi-indicator group decision-ranking system of physicians [26].

Table 5. Various factors influencing patients' choice of physician. The existing literature examines expertise, reputation, communication skills, location convenience, appointment availability, insurance acceptance, cost, recommendations, online reviews, and cultural/language preferences.

Reference	**Reputationality**						**Service**			**Affordability**			**others**	
	affiliation		reputation		word-of-mouth		experience			costs			cares	
	education	organization	position/title	achievements	online ratings	user evaluation	expertise	practices	histories	distance	expenses	following costs	privacy	discrimination
Jiang et al. [17]	√	√	√	√	√	√	√		√					
Liu et al. [68]		√	√		√									
Deng et al. [69]			√			√		√						
Li et al. [70]				√	√	√		√						
Li et al. [71]		√	√		√			√						
Li&Hubner					√									

[72]													
Xu et al. [26]			√		√			√					
Xu et al. [53]						√		√				√	
Gong et al. [73]	√	√		√	√		√						√
Ju et al. [35]				√				√	√				
Wang et al. [34]		√				√	√	√			√		
Yuan et al. [4]	√				√	√		√				√	

Reputation. "Worshiping famous physicians" has become a very common phenomenon among patients. No matter the severity or condition of the patient's disease, most patients prefer senior physicians from bigger institutions and more reputable practices [34]. The reputation of a physician is one of the most valuable attributes of a physician and plays an important role in patients' decision-making process [69]. Generally, physician reputation can be divided into two categories: offline reputation and online reputation [68]. The former is determined by the hospital's rank, academic title, professional level, the number of years in the field, and the popularity of the physician. The latter depends on patient evaluations and ratings, as well as the number of votes received, acknowledgment letters, virtual gifts, and other factors. Patients' cult of famous physicians is largely based on physicians' offline reputations. Liu et al found that the ranking of the hospital and the title of the physician had a direct impact on patients' choices. The higher the title and ranking, the more popular the individual is [68]. Deng et al also concluded that the title of the physician had a significant impact on the choice of the patient [69]. Patients favor the chief or deputy chief physician over the regular resident physician. Additionally, offline reputation can moderate the impact of online reviews on patient choice. Li et al. demonstrated that hospital rank and physician professional credentials negatively moderate the effect of physician online ratings and activity on patient choice [71]. Huang et al. revealed that a physician's high title negatively moderates the effect on physician service ratings, while positively moderating the number of service reviews [74]. Word-of-mouth in OHCs determines physicians' online reputation. The experiences of previous patients, reviews, and recommendations are important decision sources for newcomers. Deng et al. revealed that the number of views and votes received on physicians' homepages positively influenced patients' choice of physician [69]. Gong et al examined the impact of online reviews and online ratings of physicians on patient decisions from the perspective of trust theory [73]. Li et al found that positive physician reviews were positively related to a patient's choice of physician, while negative physician reviews played the opposite role, and that negative reviews had a greater impact on a patient's choice of a physician than positive reviews [71]. Li and Hubner demonstrated that patients preferred physicians with higher technical skills over those with higher interpersonal skills based on the different dimensions of physician ratings [72].

Serviceability. In regards to social exchange theory, physicians' participation in OHC is a social exchange behavior, and services such as publishing scientific articles, providing OMC services, and offering appointment registration can bring physicians financial and social rewards [6, 74]. The quality of a physician's services is reflected in patients' online ratings and post-evaluations, which in turn influence the decision to choose a physician made by potential patients in the future. Physician service quality in OHCs can be measured by the level of platform activity, engagement, responsiveness, and frequency of updating popular articles. Deng et al asserted that physicians' behaviors, such as regular updating of medical information, publication of scientific articles, and answering patients' questions, can enhance their community reputation, which in turn can attract more patients [69]. Gong et al noted that updating physicians' information frequently and providing quality online services were critical to building trust between physicians and patients [73]. Using the number of physician publications of popular articles in OHCs, Li et al found that physician activeness was positively associated with patient selection [71].

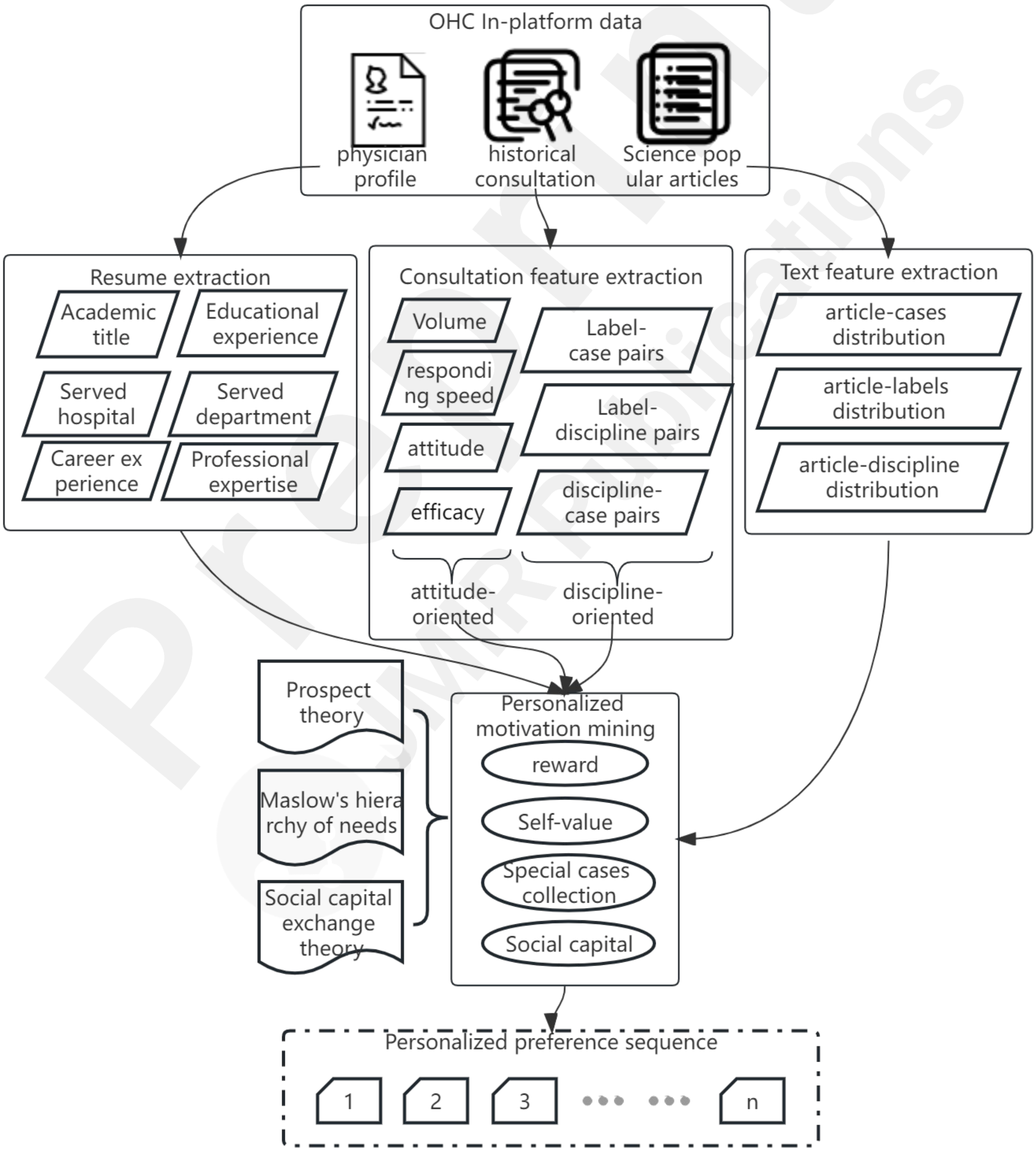
Affordability. It is also important for patients to consider the time and financial expense of visiting their physician when selecting a physician, preferring an appointment time and location that is convenient for them as well as cost-effective treatment options [25, 28]. One of the factors that patients consider when choosing a physician is the location of the physician. Typically, patients consult online before consulting offline, and the location of the OMC-receiving physician is related to the convenience of future offline consultations. Ju and Zhang considered the location of the patient to improve the convenience of combining online consultation with offline treatment [35]. Deveugele et al analyzed questionnaire data from six European countries and studied video recordings of consultations and found that the location of a physician's hospital affected the length of the online consultation [75]. Compared to geographical location, consultation costs have relatively little impact on patients' choice of OMC services. Khairat et al reported that costs were one of the primary factors determining patients' choice between mobile health and telemedicine [76]. Fletcher et al also argued that The cost of providing mental health treatment via video at home was significantly less than the cost of providing in-person care, assuming that patients can make use of existing personal technology [77].

Others. The personal characteristics of a physician, such as his or her appearance and gender, can also influence patients' choices. Ouyang and Wang found that a serious and stable physician appearance image contributes to patients' trust in physicians, which in turn influences their medical choices [78]. Additionally, patients have some stereotypes about physicians' genders. The gender difference in physicians also extends to the distinction between different departments and medical specialties. Bertakis found that male and female physicians practice in different ways [79], with female physicians providing more psychological counseling and preventive services, and male physicians focusing more on technical practices like physical examination. A physician's gender also influences patient choice. Gong et al found that physician gender influences physician ratings and patient choice, and that patient choice is enhanced when the physician is male [73].

(b)Physician preferences

Continual physician involvement is crucial to the survival, growth, and prosperity of OHCs [66]. Although patients are consumers of OHCs and physicians are merely providers, the latter is of greater significance and influence. Patients that participate in OHCs seek out famous physicians, and existing OHCs are essentially physician-driven organizations [58]. In comparison with their counterparts, physicians possess a higher level of cognition and more logical behavior. There is a relatively large amount of data on physicians in current OHCs. By mining behavioral data, it is possible to gain a better understanding of their motivations and expectations. Unfortunately, most previous studies have been primarily concerned with physicians' fitness from a professional perspective rather than their willingness and preferences from a drive and reward perspective. Current paradigms of research, which ignore the individualized preferences of the recommended population, are not adequate to meet the growing need for human-based, knowledge-based service recommendations. According to physician motivation theory, we propose a research paradigm to examine how perceptions of personal benefits and costs, satisfaction with individual needs, and cultural differences influence physicians' OMC decisions. Few studies have examined physicians' preferences, and more have discussed physicians' motivation to participate, which influences physicians' performance in OHCs. Physicians who join OHC and provide OMC services face both costs and rewards [6]. A rational decision is based on weighing the costs and benefits. Physicians incur cognitive costs, which include fatigue, pain, and irritability generated by providing knowledge-intensive and labor-intensive services, and implementation costs, which include time, material, and financial costs. physicians receive a variety of rewards, including both social and economic rewards. The former describes that a physician is respected and valued by his or her patients for the services they provide in OHC as well as for fulfilling their own needs and realizing their self-worth. The latter represents that a physician receives both direct financial gains from OMC as well as virtual gifts and bonuses from their patients. Financial and social rewards are significant factors influencing physicians' engagement in OHCs and OMCs. Physicians' expectations also influence the extent of their influence. Figure 8 illustrates how data mining of physicians who participate in OHCs and determining their motivation to participate in OMCs can be carried out. Data collected include, but are not limited to, academic titles, educational backgrounds, career experiences, scientific research accomplishments, and case characteristics associated with their historical consultations. The objective of mining these data is to develop a multidimensional preference index system for material motivation, career motivation, and social capital motivation. This will enable us to improve the adoption rate of recommendations and promote a personalized physician recommendation system.

Figure 8. Mining physician motivations and personalized preferences. The collected data, encompassing academic titles, educational backgrounds, career experiences, research accomplishments, and consultation case characteristics, inform a multidimensional preference index system. This system addresses material, career, and social capital motivations, enhancing recommendation adoption rates and personalized physician recommendations.



Motivations. Physicians' motivations for joining OHC are remarkable in their diversity. Physicians are not only concerned with financial rewards, but also with career planning, professional reputations, and social capital. These considerations include the need for self-worth realization, prestige, social support, and personal branding [66, 80]. Maslow's needs theory suggests that prestige contributes to self-realization. Social exchange theory also reveals that self-realization, prestige, and social support positively influence physicians' willingness to provide online services, while executive costs negatively impact their willingness to do so. Using expectancy theory, Chen et al found that both external motivation, e.g., external rewards and expected relationships, and intrinsic motivation, i.e., a sense of self-worth, positively influenced physicians' willingness to provide consultation services, while consultation time, as a major cost, negatively moderated the relationship between physicians' willingness to serve and behavior [66]. Zhou et al combined mental health-related OHC with motivation theory and demonstrated that both intrinsic motivations (technical competence) and extrinsic motivations (network reputation and financial rewards) positively influenced psychologists' voluntary behaviors [81]. Yang et al suggested that physicians' contributions to OHCs were positively influenced by both personal and social motivations, and physicians' professional titles moderated this effect, with physicians with high titles emphasizing reputation and physicians with low titles emphasizing monetary rewards [82]. Zhang et al found that when physicians reach an advanced level of expertise and knowledge, their material motivation declines and their professional motivation increases [3]. Some physicians place great emphasis on personal branding, and their online services are designed to support their brand positioning and identity. Zhang et al indicated that the OHC environment impacts brand performance, including trust and reputation, which become more significant factors in determining whether physicians participate in a consultation [83].

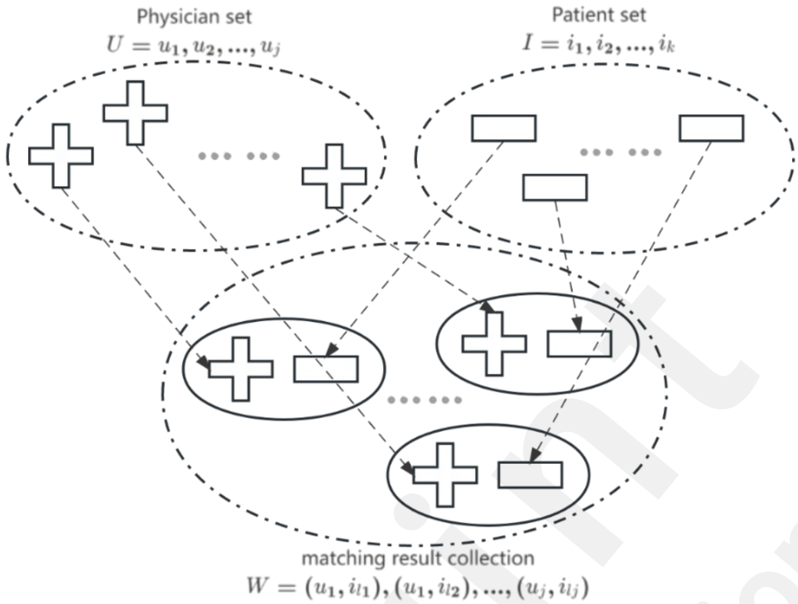
Economic returns. Most physicians provide OMC services for financial reasons. OHCs need to understand how to improve financial rewards for physicians to retain good physicians. Ren and Ma investigated the factors influencing physicians' economic income in OHCs in the context of the pandemic [42]. They found that service quality had a significant positive effect on physicians' economic returns. Additionally, they found that physician teams increase income with disease privacy, and physicians who established a team were more likely to earn more money. On OHCs, physicians share articles about health and medicine, as well as provide paid OMC services. According to the literature [3], physicians share free messages due to both material and professional motivation, with the role of material motivation diminishing as physicians gain more expertise. Zhang et al reported that mutual aid and altruism can positively influence the willingness of health experts to share knowledge [80]. In addition, reputation and self-efficacy can play a greater role in health experts' willingness to share knowledge than regular users. Yang et al demonstrated that physicians are motivated to share paid messages for a variety of reasons [82]. External motivation, enjoyment motivation, and professional motivation are all important factors.

Social rewards. According to the literature [41], social rewards have less influence on physician motivation than financial rewards. A combination of psychological and material rewards increases physician motivation to participate in OHCs. Material rewards are usually more useful than psychological rewards, but extreme rewards are less effective than moderate rewards. To increase physician stickiness, OHCs often include gamification elements such as badges, points, and leaderboards. Liu et al observed that including gamification elements in medical communities can encourage continued participation and increase physician incomes, but on the other hand, gamification elements can also lead to greater income disparities among physicians [84].

Two-sided matching

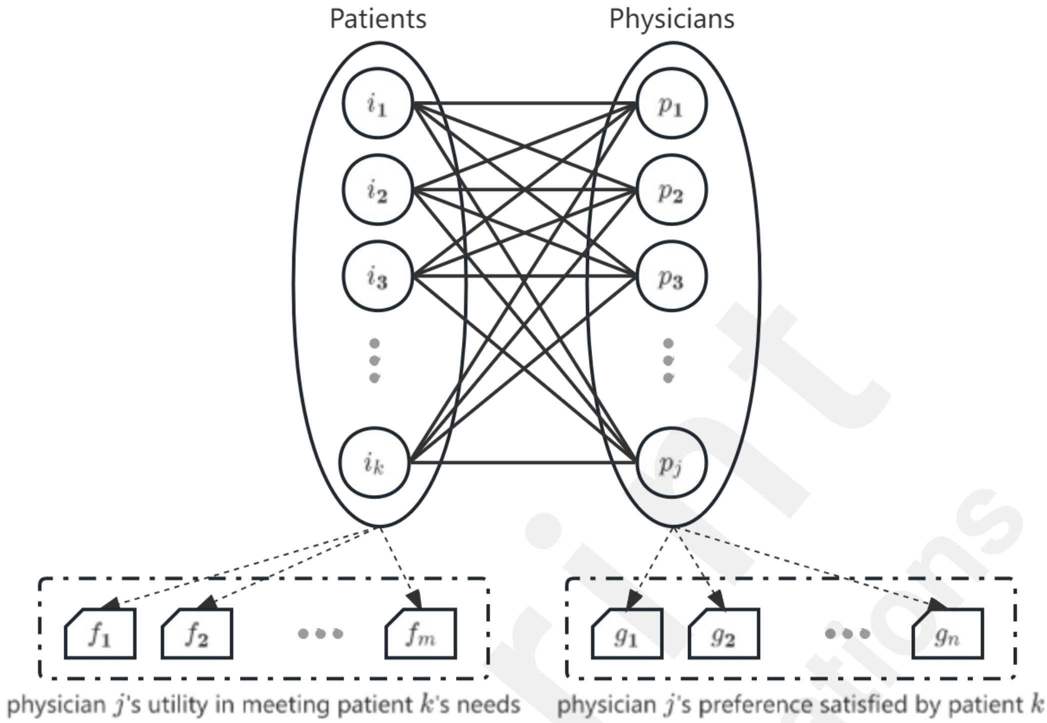
Unlike the previous studies, this paper focuses on the personalized service recommendation system for two-sided users. It is not just about providing patients with a list of physicians but exploring the overall combination solutions with optimal mutual benefits for both patients and physicians, shown in figure 9. Several important issues need to be addressed by researchers in this field, including the adoption of appropriate decision methods that effectively match the interests and preferences of both physicians and patients, improve the adoption rate of recommended solutions, and enhance the satisfaction of two-sided users [85]. Xi and Juan addressed the real problem of matching the supply and demand of healthcare services under an intelligent platform and proposed a decision-making method that takes into consideration the subject's expectations as well as the psychological characteristics of hesitation and uncertainty [85]. Gao et al analyzed the problem of matching decisions for medical services in OHCs and constructed a matching decision model that is both satisfactory and stable [86]. Zhong and Bai analyzed the patient-physician preference matrix and constructed a two-way matching model for specialty outpatient appointments oriented toward satisfying patients and physicians [87]. Yang et al used the two-sided matching theory to design a patient-specialist paired appointment system [88], in which the appointment process and the one-to-many appointment matching algorithm were described. Chen et al developed an innovative multi-attribute decision-making method for two-sided matching [89], taking into account the psychological behaviors of matching bodies, as well as values of aspiration levels and evaluations.

Figure 9. Service-oriented recommendations aim for more than just listing physicians for patients; they seek comprehensive solutions that benefit both parties. This concept is illustrated in a Physician-Patient Matching diagram.



The future research direction of the physician-patient two-sided matching recommendation system should take into account the decision-making environment of realistic situations. As an example, due to the complexity of medicine and the ambiguity of human thinking, most patients are unable to clarify clear preference sequences due to their cognitive limitations. By mining consultation text and behavioral characteristics of OHC users, the OMC recommendation system should capture customized preference sequences. Even for physicians, who have higher cognitive levels, more logical behavior, and clearer motivation, there are still situations where expectation evolution and multiple preferences cannot be ordered. Therefore, the recommendation system must accommodate their intuitive fuzzy preferences. Using intuitive fuzzy preferences, biased order relations can be expressed and preference strengths can be differentiated. Figure 10 illustrates how an intuitionistic fuzzy set matrix is transformed into a satisfaction matrix. The system should then construct a multi-objective optimized stable two-sided matching model based on intuitionistic fuzzy number information with the objectives of maximizing physician-patient matches, stability, and satisfaction with the matching results.

Figure 10. Modeling of physician-patient personalized preference order maximization. The recommendation system transforms an intuitionistic fuzzy set matrix into a satisfaction matrix and constructs a multi-objective matching model. It aims to maximize physician-patient matches while ensuring stability and satisfaction.



Workload balancing

Physicians, as humans, have not only individual drivers and preferences, but also variability in load tolerance. The fact that the recommended ones represent a limited human resource has generally been overlooked in previous studies. Physicians could not overwork and they should not be overused for an extended period [34]. Physician overload affects physician fatigue and consultative quality, as well as patient waiting time, which deteriorates the comprehensive evaluation of the recommendation system [25]. Currently, very few studies have explicitly considered the workload of recommended physicians in recommender systems. To address the problem of unbalanced utilization among physicians, Pan et al added a balanced utilization approach (utilization balancing) to a preference learning algorithm that included a negative penalty term for physicians whose current utilization exceeded the mean value [25]. To balance patient preferences and hospital staff workload, Wang et al developed an utility-diversity trade-off model based on physician capacity, patient preference, and outpatient workload, which has the effect of reducing the workload for highly regarded hospitals and physicians [34]. Yuan and Deng suggested that limiting the number of times a physician is recommended could balance the workload while exposing more people to new physicians who could also share the workload [4]. In addition to reducing the workload of chief physicians, Yang et al increased the number of recommendations to new physicians, which translates into a saving of time and money for patients [28]. The system could also be used to identify the activity of each physician's intake based on historical consultations obtained from

OHC, which, we believe, represents a difference in the upper limit of the workload of individual physicians, which is influenced by the physician's age, specialty department, as well as the number of offline consultations he or she has received.

The load balancing of OMC service recommendations is similar to personalized re-ranking, which generally refers to ranking items in the recommendation result list based on the user's preference. Based on the recommendation results list, load balancing attempts to determine the workload of each recommended physician, adjust the list order or replace the candidate physicians according to their predefined individual thresholds, so that the recommendations are achieved as efficiently as possible. The re-ranking algorithms typically use two categories of indicators: first, they integrate the re-ranking indicators directly into the recommendation algorithm to train a multi-objective model; secondly, heuristics are used to optimize the re-ranking indicators using a two-stage approach of filtering and re-ranking, followed by optimization of the load balancing. Among the integrated algorithms, Adomavicius presented heuristic neighborhood techniques and matrix decomposition techniques to generate a more diverse set of recommendations with a lower workload for each physician [57]. Pedronette and Torres proposed a method for reordering image content retrieval systems that combined recommendations with clustering and encoding context through ranking lists [90]. Among the two-stage algorithms, Yu et al investigated the relationship between recommendation accuracy and diversity and proposed an adaptive trust-aware recommendation model to improve cold-start and long-tail items [91]. In the literature [29], a dynamic exponential inventory balancing algorithm for recommendations is presented based on the condition that physician resources are limited in a dynamic environment, and based on real-time remaining resources, it presents a dynamic exponential inventory balancing algorithm. In a static environment, the physician recommendation system can be improved effectively by utilizing the heuristic algorithm SORT, which can be used in cases where resources are insufficient. Wang et al developed two heuristic algorithms for balancing patient preferences and hospital staff workload, as well as updating physician rankings without changing physician capabilities so that patients can access more skilled physicians in more hospitals [34]. In summary, the algorithms differ depending on the application scenario. Based on historical data, we can determine physicians' work tolerance levels by mining historical data; to optimize recommendation results, we can personalize constraints on physicians' upper limit of workload; and dynamically optimize between patients' needs and physician energy so that the results are maximized while maintaining the quality of recommendations and reducing the workload of physicians. Using these ideas can reduce the waiting time for patients and ease the strain on physician resources.

Privacy protection issues

National legislation to protect user privacy in the healthcare sector is among the most stringent [26, 81]. OMC service recommendations can only use anonymized, scrambled, encrypted, and other technically processed historical data. Consequently, it is difficult to obtain an individual identifier for each patient in the dataset, which limits the algorithmic mining of patient features. Further, national regulations regarding the prevention of leakage and misuse of personal information are becoming increasingly strict, and all personalized recommendation systems must and can only conduct legitimate research following user privacy protection [64]. Technically, collaborative filtering models are not suitable for OMC recommendation scenarios, regardless of whether they are based on user-CF or term-CF. A user is unlikely to seek help online unless he or she is ill or experiencing certain symptoms. The specialty of physicians that patients seek out is therefore not determined by their explicit or implicit interests, but rather by their medical needs at that time. The concept of ”inferring future needs from patients' historical data” is not logical in the context of the OMC service scenario. Unfortunately, some existing studies continue to attempt to mine peripheral information and even private information from patients, which is both illegal and ineffective. Simply reusing collaborative filtering from e-commerce recommendations and recommending physicians based on historical patient data, regardless of containing medical privacy or not, will ruin personalized e-service recommendations. Xu et al proposed an effective and privacy-preserving medical service recommendation scheme that identifies patients' demands with physicians' information, along with their reputation score, which is seen as the first study to develop a physician recommendation scheme that ensures computational efficiency [26]. Similarly, to ensure patient privacy, Narducci et al constructed a semantic recommendation system that does not link the health data entered by patients to their true identities [19]. Since user information is protected by regulations, patient consultations contain only isolated texts and graphics related to disease descriptions. Additional information is lacking, potential preferences are unclear, and invisible needs are not addressed comprehensively. As a means of achieving intelligent recommendations under privacy protection, the system must “dance with shackles on”. To guide personalized preference mining, engineering psychology theories would be better applied, followed by natural semantic processing tools, topic models to refine patient descriptions, and semantic mining to quantify qualitative indicators. Patients' social networks and multi-modal interaction sessions in OHCs would be better collected through this system, as well as identifying potential preferences, qualitative indicators, quantitative indicators, and perceptions of patients through natural language processing, multi-modal data analysis, and heterogeneous dynamic network mining.

Contributions and Limitations

(a)Theoretical Contributions

The review highlights a significant gap in research regarding service-oriented recommendations within OHCs. While OMCs are widely used on the internet, there is a notable scarcity of corresponding research on service recommendations within these environments. Traditionally, research in OMC recommendation systems has followed the conventional e-commerce model, focusing on recommending "items" to "users" rather than customizing e-service recommendations, such as recommending "users" to "users." This lack of focus on personalized service recommendations limits the potential for enhancing user experience within OHCs. Moreover, existing recommendation algorithms primarily focus on mining, modeling, and matching expert knowledge, neglecting the consideration of two-sided user preferences and the workload of service providers. This oversight can result in recommendations that do not effectively cater to the needs and preferences of both service providers and consumers within OHCs.

Another crucial aspect highlighted in the review is the limited consideration given to the cognitive capabilities of service consumers. Current recommendation algorithms often fail to adequately address the issue that service consumers may lack professional cognitive capabilities. Adopting interpretable recommendation algorithms could help bridge this gap and improve the effectiveness of service recommendations within OHCs. Furthermore, the review emphasizes the importance of using consumer comments judiciously in the recommendation process. While consumer comments can provide valuable insights, they should be analyzed with caution to ensure the reliability and relevance of the recommendations generated.

In summary, research on personalized recommendations for online knowledge services within OHCs is still in its early stages, facing challenges such as the "cold start" problem and the lack of a theoretical framework or algorithm. Addressing these challenges is crucial for advancing the field and enhancing the quality of service recommendations within OHCs.

(b)Practical Enlightenment

The practical implications of the review findings are twofold and can greatly benefit stakeholders within OHCs. Firstly, the insights provided by the review can aid OHC stakeholders, including platform administrators and policymakers, in evaluating and optimizing the design of recommender systems. By understanding that service-oriented recommendation systems should function as two-sided matching systems rather than just expertise retrieval systems, stakeholders can make informed decisions about system design and implementation. This understanding can lead to the promotion of policies that prioritize the consideration of two-sided preferences, thereby enhancing user satisfaction and engagement within OHCs.

Secondly, the review findings can assist developers in prioritizing their work and implementing measures to address key challenges faced by OHCs. For instance, developers can focus on enhancing workload balancing for physicians by optimizing recommendation algorithms to consider both the workload of service providers and the preferences of service consumers. Additionally, developers can implement measures to protect patient privacy while still providing personalized recommendations, thereby fostering trust and confidence among users.

Overall, the practical value of the review findings lies in their ability to guide stakeholders and developers in optimizing the design and functionality of recommender systems within OHCs, ultimately leading to improved user experiences and outcomes.

(c) Limitations and Future Work

The primary limitation stems from the relatively small number of studies included in the meta-analysis, resulting in less robust synthesized results. Despite a growing body of research on physician recommendations, there remains a scarcity of strictly designed OMC-oriented recommender systems. Notably, while online medical applications are widely used in China, this review excludes papers published in Chinese due to language constraints.

Conclusion

Recent years have seen an explosion of interest in physician recommendations, largely driven by the spread of OHCs and the success of artificial intelligence in other fields. As a result of the emergence of OMC, an online service, physician recommendations have moved into a new age. These new-generation recommendation systems are service-oriented rather than commodity-oriented and build on the concept of two-sided markets. That synergizes both patients and physicians with their needs and preferences individually, inspiring e-Service recommendation thinking, vision, paradigms, approaches, and practices. The study has a distinctive pioneering character, and it is expected to open up a new branch of recommendation system theory. The e-Service-oriented recommendations demonstrate their transformational, transdisciplinary, and translational features in terms of thinking, paradigms, methodologies, technologies, engineering, and practices. The paradigm shifts and directions are discussed in this paper. Unlike traditional e-Commerce recommendations, e-Service recommendations emphasize big-picture, outside-the-box thinking as well as data-driven, model-based, two-sided hypotheses, which pursue foundational and original recommendation thinking, theories, and practices from the essence of knowledge-intensive and labor-intensive services inherent in the knowledge economy.

Acknowledgments

This project is supported by the Fundamental Research Funds for the Central Universities, and the

Research Funds of Renmin University of China (Grant number 23XNL017)

Data Availability

The data sets collected and analyzed during this study are available from the corresponding author upon reasonable request.

Authors' Contributions

HJ and WX contributed to study conception and design. HJ and ZM collected, analyzed, and interpreted the data. HJ drafted the manuscript, and WX was responsible for its critical revision.

Conflicts of Interest

None declared.

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Abbreviations

Analytic hierarchy process	AHP
Association for computing machinery	ACM
Bidirectional encoder representations from transformers	BERT
Collaborative filtering	CF
Decision tree	DT
Grading of recommendations, assessment, development, and evaluations	GRADE
Intuitionistic fuzzy numbers	IFNs

Knowledge graph	KG
Latent dirichlet allocation	LDA
Long-term short-term memory	LSTM
Neural network	NN
Natural language toolkit	NLTK
Online health community	OHC
Online medical consultation	OMC
Preferred reporting items for systematic reviews and meta-analyses	PRISMA

Supplementary Files

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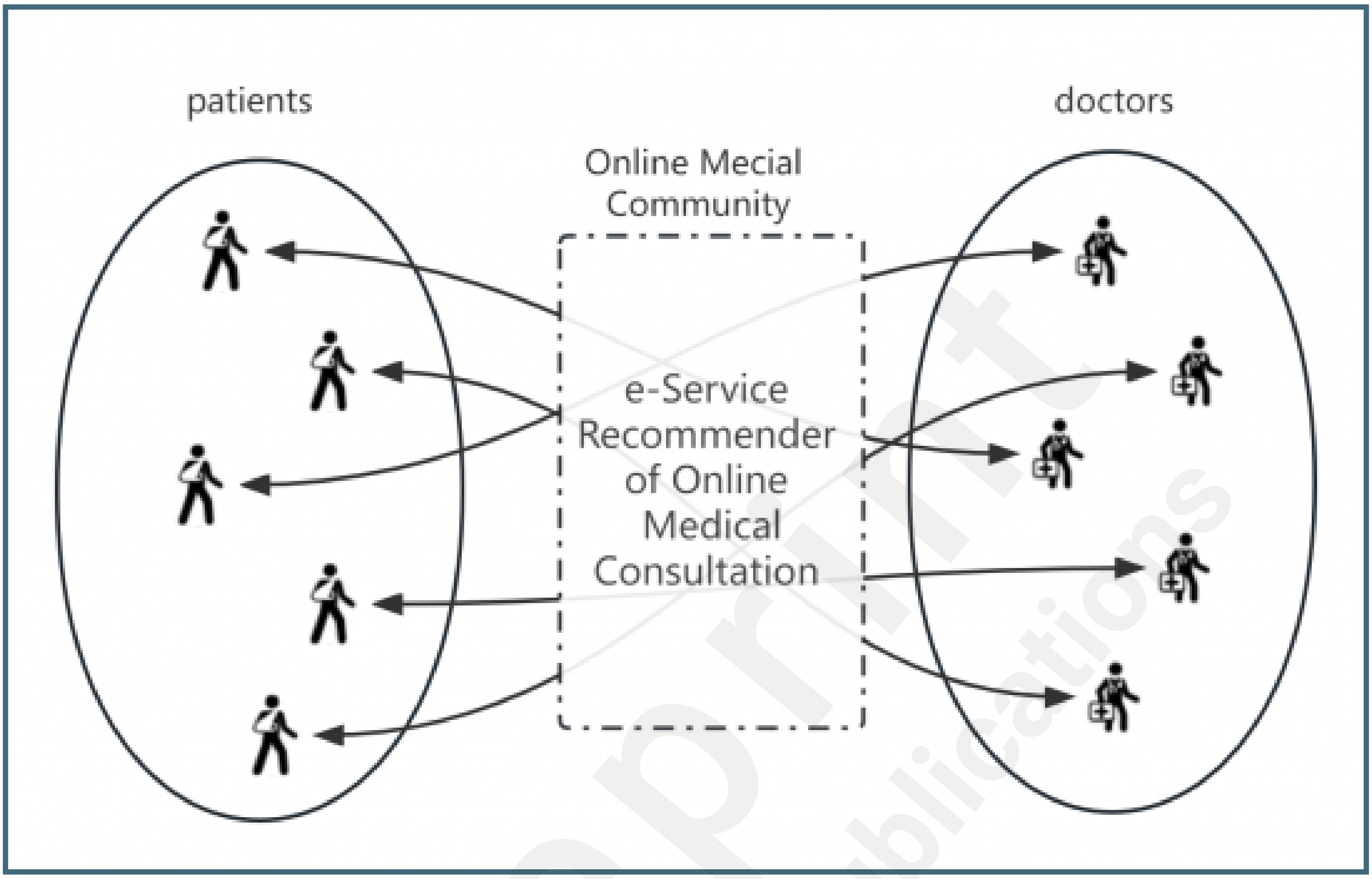
patients
doctors
Online Mecial
Community
e-Service
Recommender
of Online
Medical
Consultation

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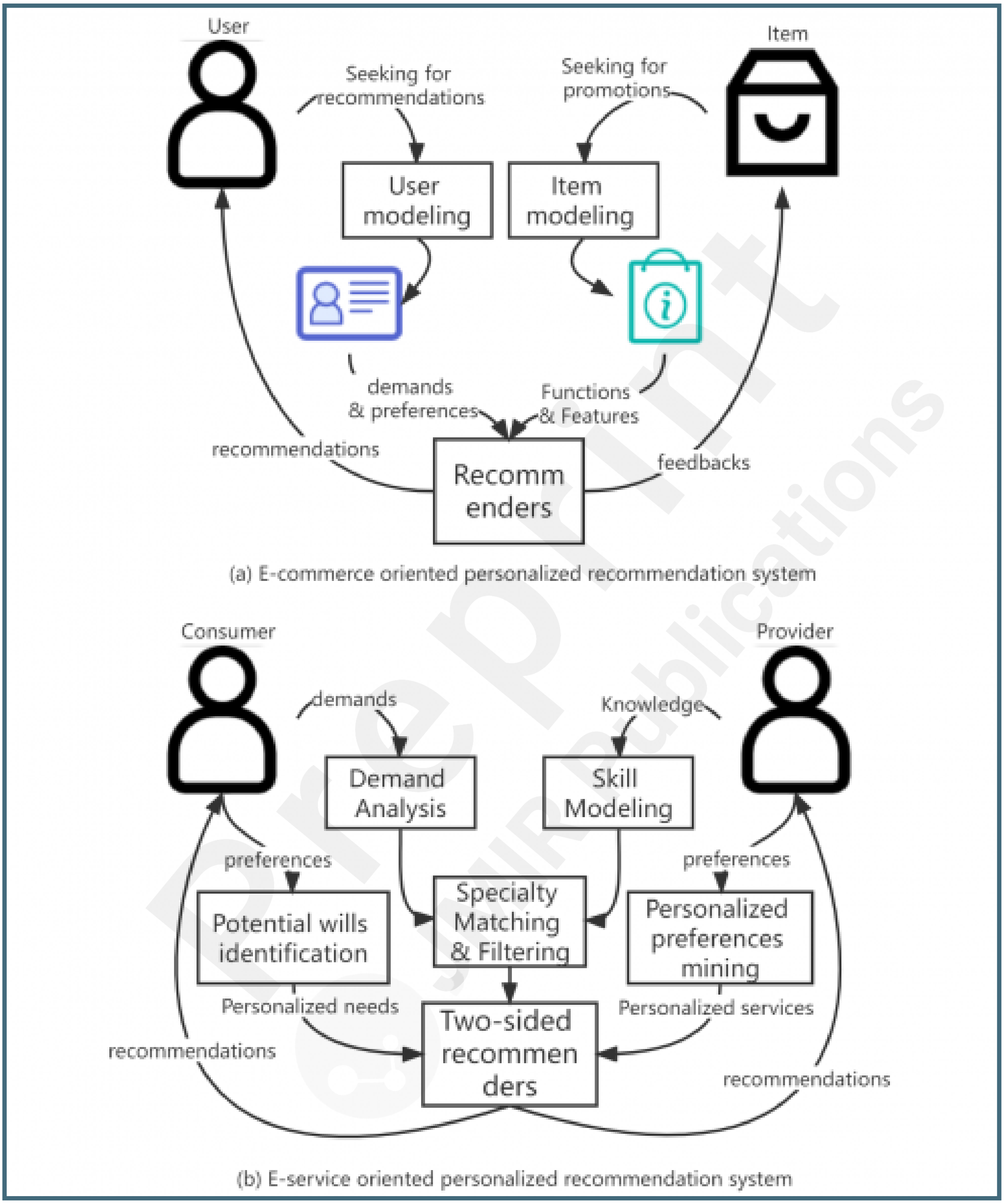

(a) E-commerce oriented personalized recommendation system

(b) E-service oriented personalized recommendation system

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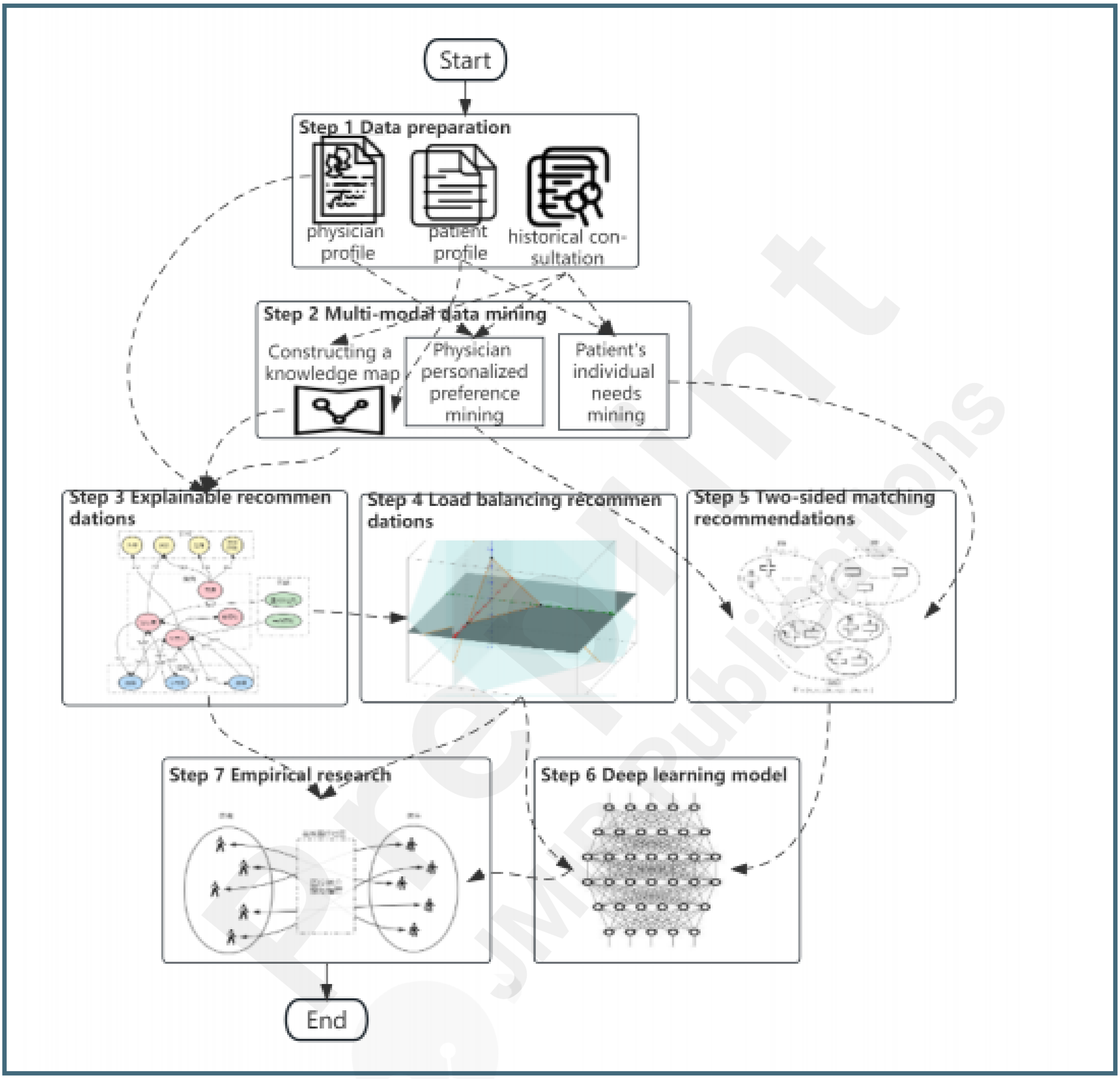
Start
Step 1 Data preparation
physician profile
patient profile
historical consultation
Step 2 Multi-modal data mining
Constructing a knowledge map
Physician personalized preference mining
Patient's individual needs mining
Step 3 Explainable recommendations
Step 4 Load balancing recommendations
Step 5 Two-sided matching recommendations
Step 7 Empirical research
Step 6 Deep learning model
End

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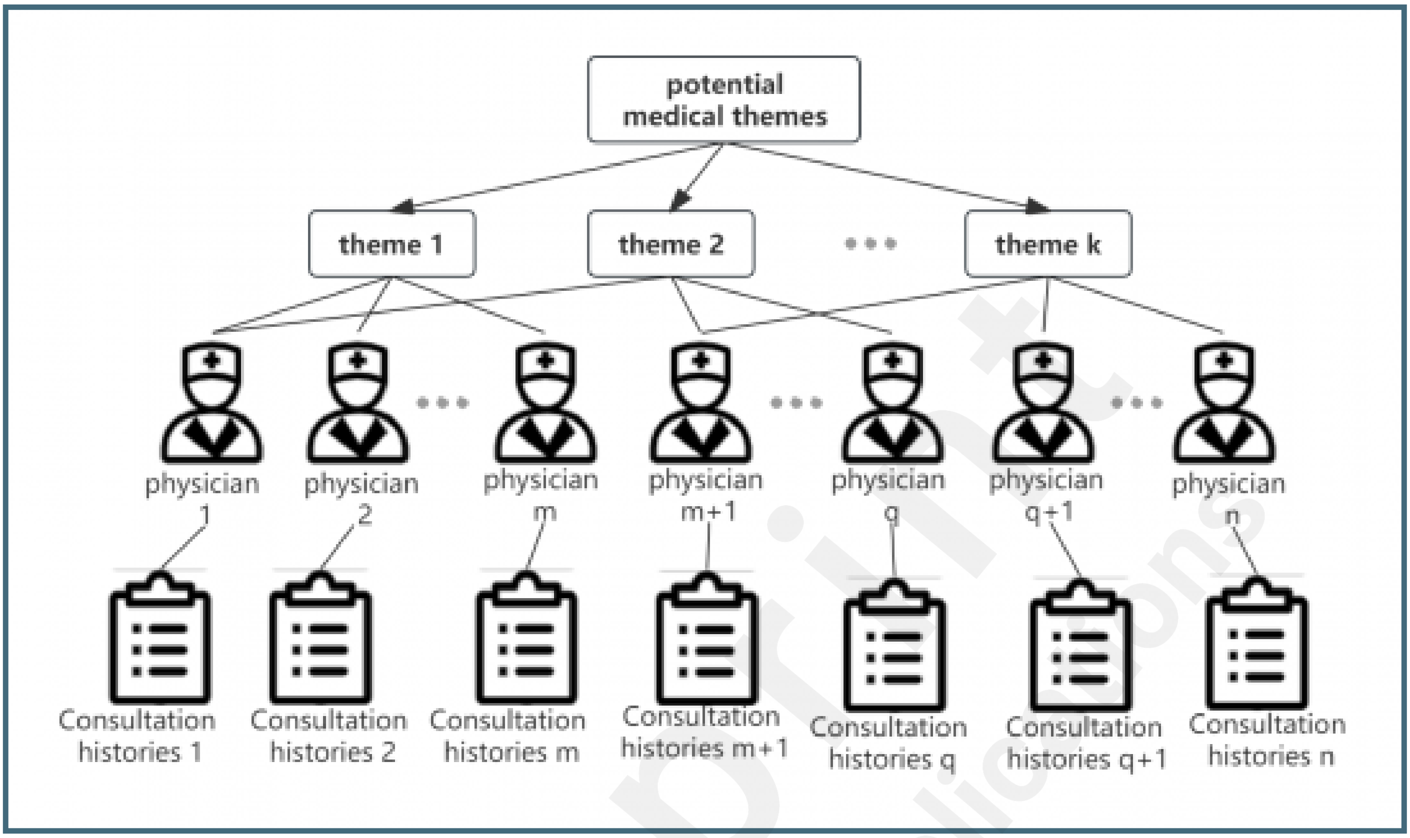
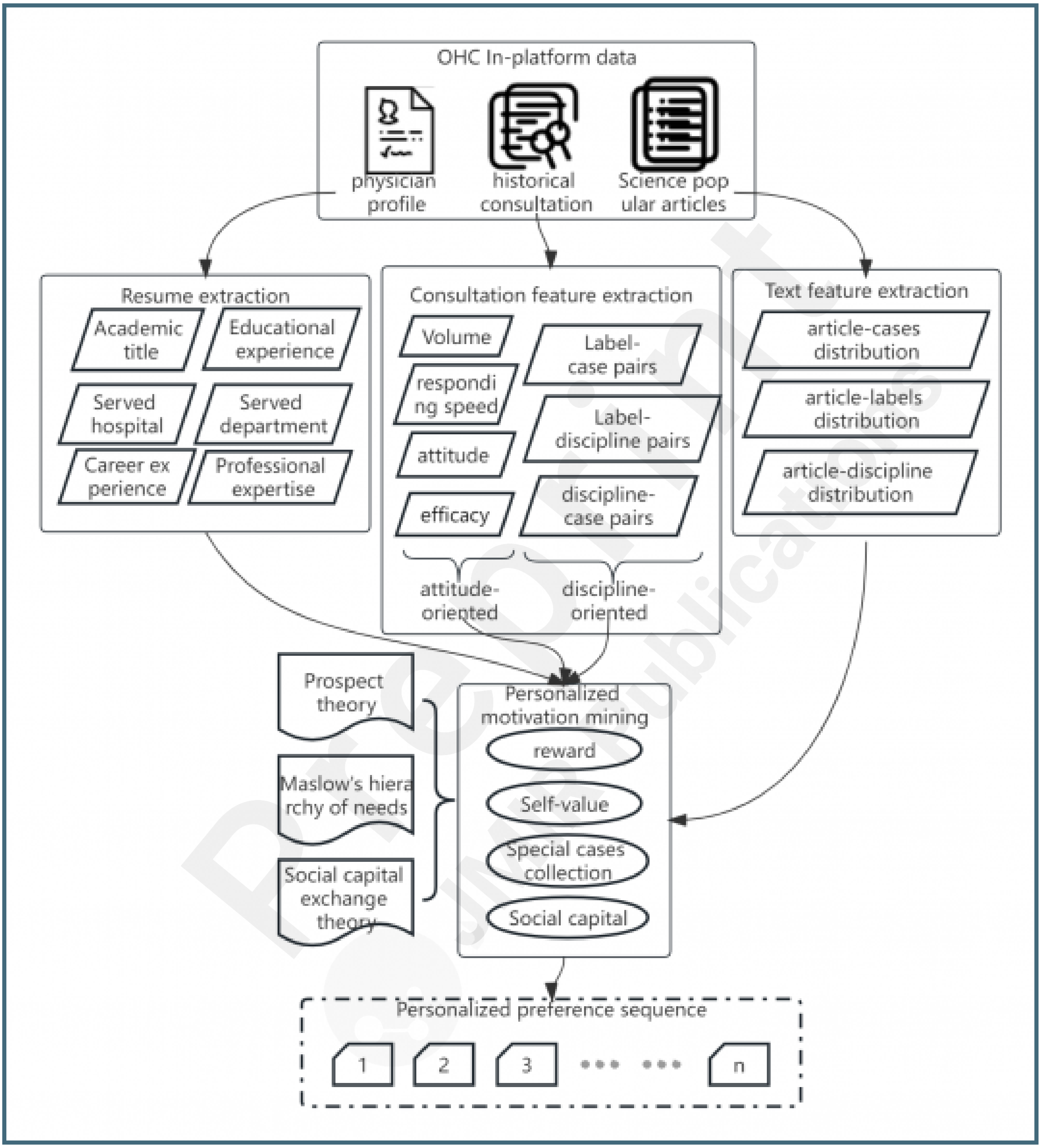
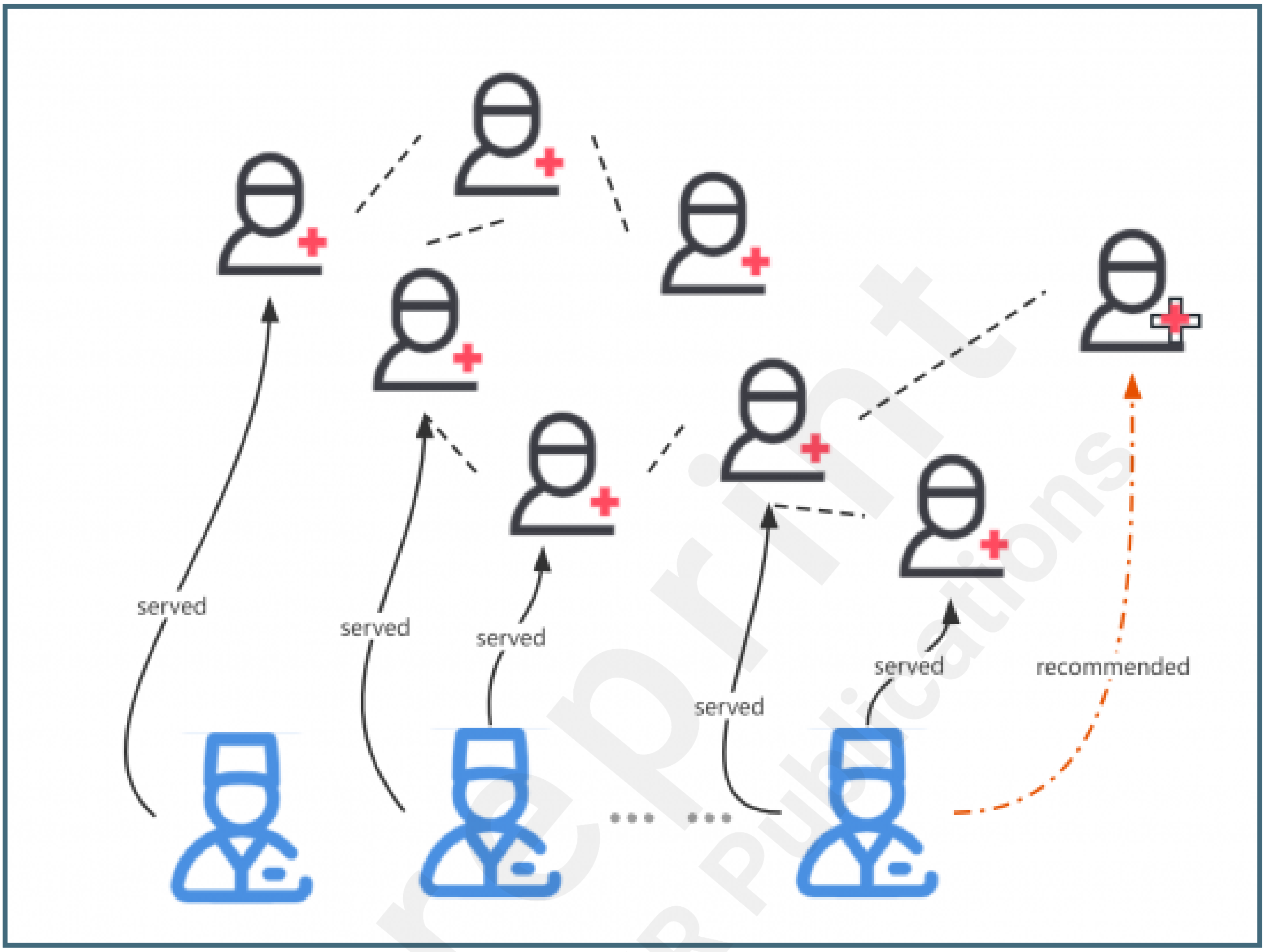

potential medical themes
theme 1
theme 2
theme k
physician 1
physician 2
physician m
physician m+1
physician q
physician q+1
physician n
Consultation histories 1
Consultation histories 2
Consultation histories m
Consultation histories m+1
Consultation histories q
Consultation histories q+1
Consultation histories n

Untitled.


OHC In-platform data
physician profile
historical consultation
Science pop ular articles
Resume extraction
Academic title
Educational experience
Served hospital
Served department
Career ex perience
Professional expertise
Consultation feature extraction
Volume
respondi ng speed
attitude
efficacy
Label-case pairs
Label-discipline pairs
discipline-case pairs
attitude-oriented
discipline-oriented
Text feature extraction
article-cases distribution
article-labels distribution
article-discipline distribution
Prospect theory
Maslow's hiera rchy of needs
Social capital exchange theory
Personalized motivation mining
reward
Self-value
Special cases collection
Social capital
Personalized preference sequence
1
2
3
n

Untitled.



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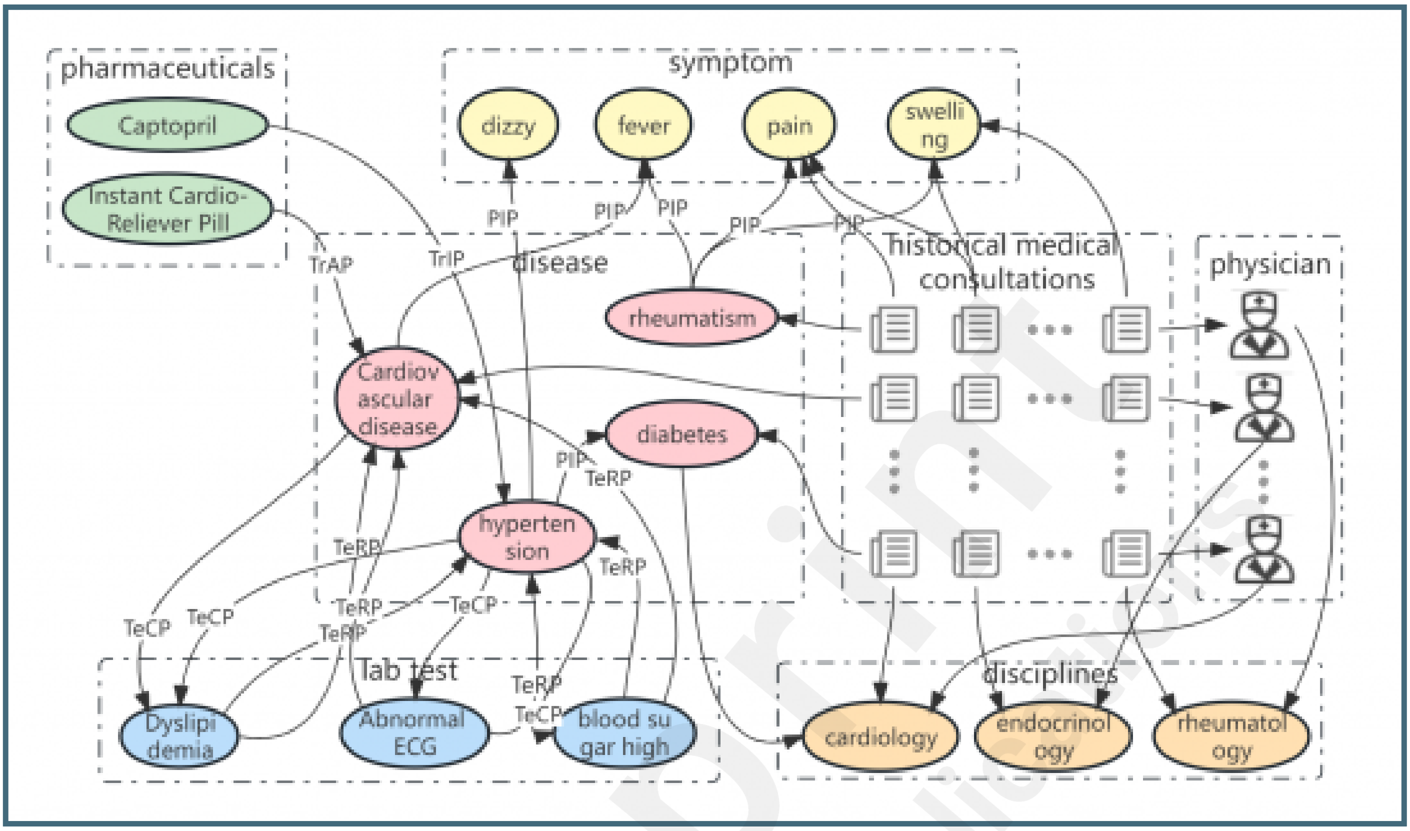
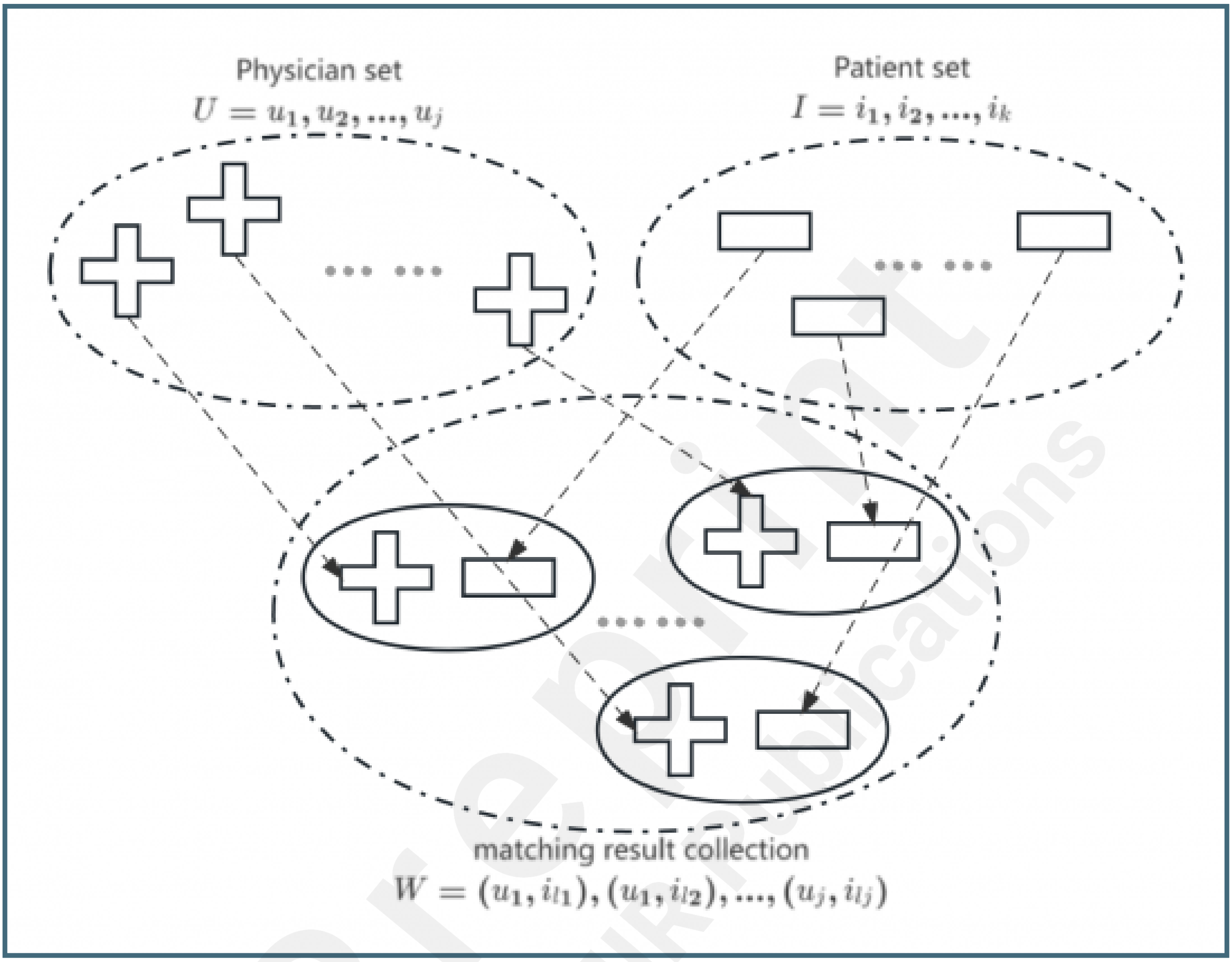
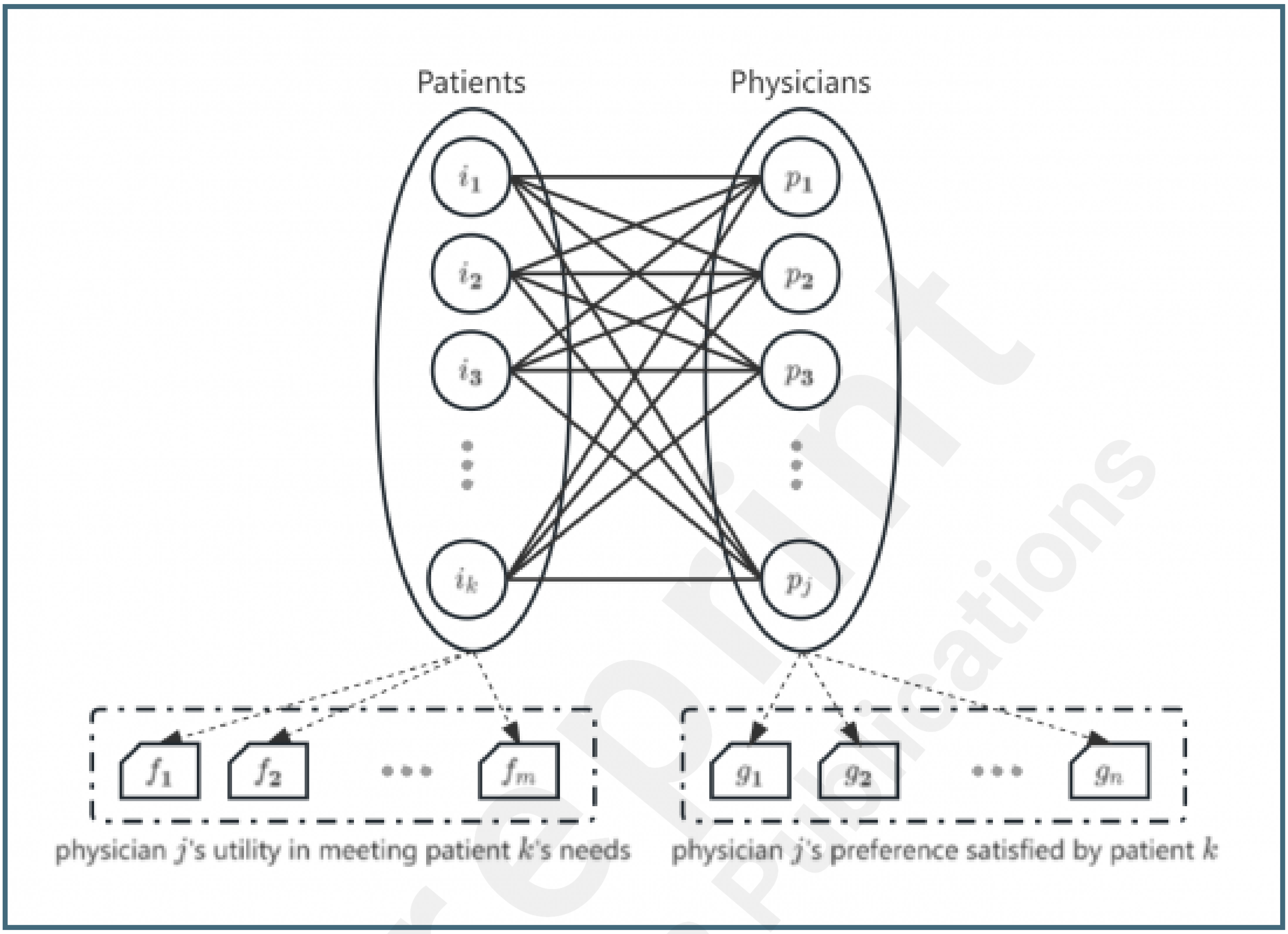

pharmaceuticals
Captopril
Instant Cardio-Reliever Pill
symptom
dizzy
fever
pain
swelling
disease
rheumatism
Cardiovascular disease
diabetes
hypertension
historical medical consultations
physician
Tab test
Dyslipidemia
Abnormal ECG
blood sugar high
disciplines
cardiology
endocrinology
rheumatology
TrAP
TrIP
PIP
TeRP
TeCP

Untitled.

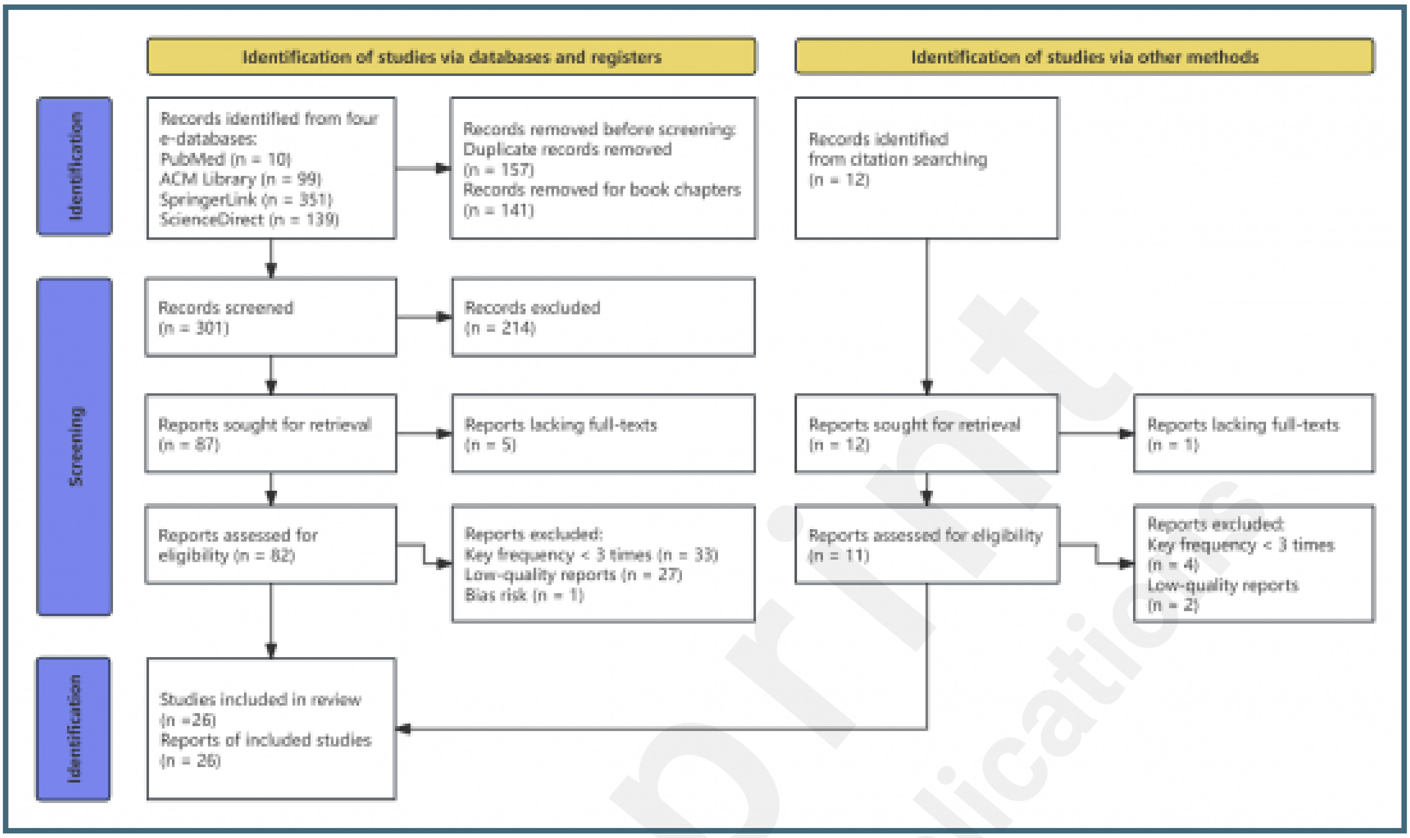

Physician set
$U = u_1, u_2, ..., u_j$
Patient set
$I = i_1, i_2, ..., i_k$
matching result collection
$W = (u_1, i_{l1}), (u_1, i_{l2}), ..., (u_j, i_{lj})$

Untitled.


Patients
Physicians
i_1
i_2
i_3
i_k
p_1
p_2
p_3
p_j
f_1
f_2
f_m
g_1
g_2
g_n
physician j's utility in meeting patient k's needs
physician j's preference satisfied by patient k

Figures

PRISMA (Preferred Reporting Items for Systematic Review and Meta-Analysis) diagram of the study.



Multimedia Appendixes

PRISMA 2020 Checklist.
URL: http://asset.jmir.pub/assets/5d7cdd09399dfc22793cca7e7bc672e3.docx