Online Medical Consultation Service-Oriented Recommendations: Systematic Review

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

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Abstract

Background: A growing telehealth industry, the online health community (OHC) bridges the gap between physicians and patients by offering an e-service of a new sort through telemedicine - online medical consultation (OMC), a solution that alleviates problems associated with unbalanced distribution and inadequate high-quality medical resources.

Objective: A personalized recommendation for OMC services is imperative to reduce patient information overload and optimize physician resource utilization. This paper aims at providing an overview of current trends and outlining e-Service-oriented paradigms and approaches to recommending OMCs.

Methods: Our systematic literature search was limited to quantitative, qualitative, and mixed-method papers published from 2001 to 2020 through ACM Digital Library, EBSCO, Springer, PubMed, and Google Scholar. Using cross-disciplinary literature on medicine, information systems, and artificial intelligence, this paper summarizes personalized recommendations for online services, which involve many aspects, such as two-sided matching for patients and physicians, interpretable recommendations for patients, and workload balancing for physicians.

Results: The paper finds that e-service-oriented recommendations are an emerging concept that has not yet been clearly defined and fully investigated. We try to break the inertia associated with tinkering with the traditional personalized recommendation models, establish an innovative theoretical framework for e-service-oriented recommendations, and propose some critical technical issues of two-sided personalized recommendations.

Conclusions: OMC is a knowledge-intensive and labor-intensive service, where patients lack expert knowledge and demand interpretable recommendations; physicians have varied energy levels and cannot afford overwork. E-service recommendations need to face two-sided users with different cognitive abilities, expectation levels, decision-making perspectives, and preferences, so they require an entirely different paradigm needs to develop distinct attributes and study unique contents.

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

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Keywords

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

1. 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 seek information and treatment from physicians through online health communities (OHCs). Meanwhile, physicians are providing the public with health and even medical information (Zhang et al., 2020a; Yang et al., 2021). 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 still contributes to the growing problem of information overload, as there are too many candidates to choose from, which exacerbates the level of hesitation (Yuan and Deng, 2022). The difficulty is compounded by the lack of medical professional knowledge and the limitations of cognitive ability that prevent patients from choosing suitable physicians on their own. An OMC-oriented recommendation system is needed that provides patients with a professional, accurate, and responsible referral process and ends up with qualified and suitable physicians.

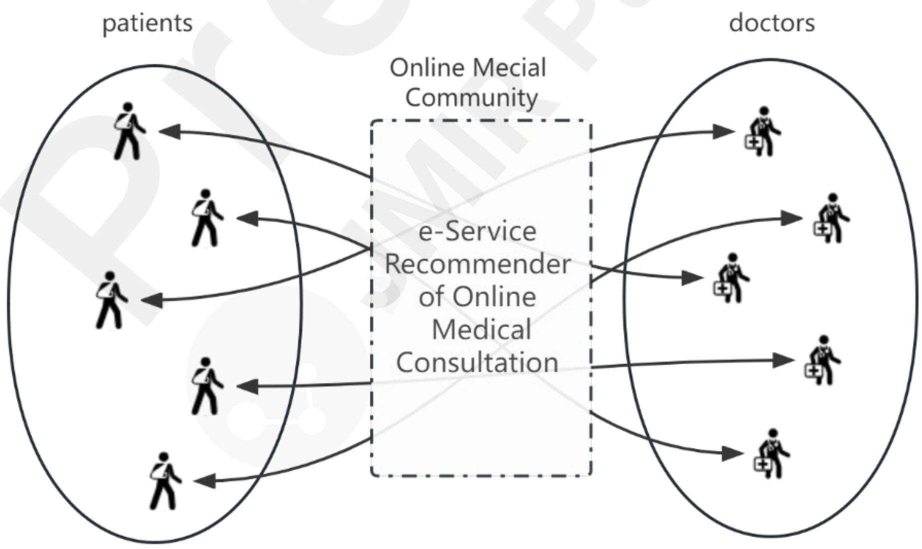

Figure 1: A two-sided OMC scenario of patients and physicians.

Most existing studies of physician recommendations are in the wrong direction, regardless of their methodology, 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 (Malgonde et al., 2020). 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(Guo et al., 2017). 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.

2. OMC recommendations characteristics

Personalized recommendation studies previously focused on commodity recommendations based on ”Users versus Items” and rarely considered service recommendations based on ”Users versus Users”. Human carriers like OMCs are highlighted in this paper 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 2 shows that a knowledge service-oriented recommendation differs from a traditional commodity-oriented recommendation from a system thinking perspective.

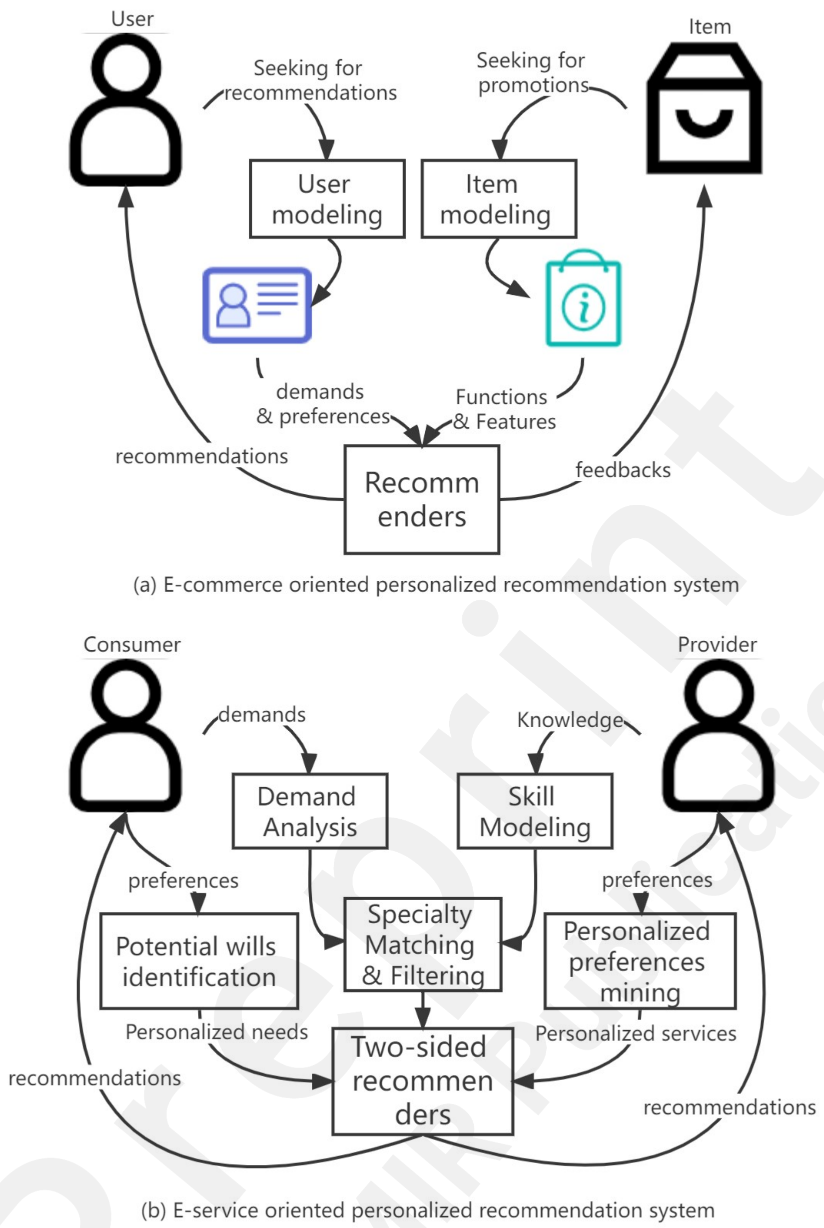

Figure 2: General comparison of the pattern of commerce v.s. service recommendation.

An independent service-oriented recommendation system requires a novel theoretical framework and its key techniques. Table 1 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 (Liu et al., 2020b). 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 1: Commerce-oriented v.s. service-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(Yuan and Deng, 2022). 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(Qian et al., 2013). 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(Xu et al., 2019a). 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(Yuan and Deng, 2022).

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(Wan et al., 2021), 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 unsuccessfulWidmer et al. (2018); Daskivich et al. (2018). 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 Zhang et al. (2020b) found no significant correlation between patients’ online reviews and their clinical outcomes. Secondly, physicians will vigorously resist unprofessional, emotional, and malicious reviews that can harm their professional reputation (Menon, 2017), 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(Lu and Rui, 2018). 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.

In summary, despite the widespread use of knowledge services, such as OMCs, on the Internet, the corresponding research on service recommendations is extremely scarce. Currently, OMC recommendation research still refers to the traditional e-commerce idea of recommending ”items” to ”users” rather than customizing e-service recommendations of recommending ”users” to ”users”. Additionally, it differs from other expert recommendation applications. It is crucial to recognize that physicians have their wishes and preferences and that the workload can not exceed a certain level. Existing recommendation algorithms are limited to mining, modeling, and matching expert knowledge, which does not take into account the two-sided users’ preferences or the workload of service providers. Further, the issue that service consumers lack professional cognitive capabilities has not been adequately addressed by adopting interpretable recommendation algorithms. Last but not least, consumer comments should be used with caution. Research on personalized recommendations for online knowledge services with humans as carriers is still in the ”cold start” phase, and neither a theoretical framework nor an algorithm exists.

3. E-service recommendation definition

In theory, an e-service recommendation system can be described as a logical mapping between two sets of two-sided users, i.e., the consumer set U and the provider set I. Let f represent the utility function that measures how well a service provider i can meet the needs of a consumer u, that is $f: U \times I \to R$, in which R represents a range of non-negative real numbers expressing the level of recommendation from I to U. Let g

be the utility function that measures how well a consumer u meets a service provider i's preferences, that is $g: I \times U \rightarrow S$, in which S represents a range of non-negative real numbers expressing the level of recommendation from U to I. In the intersection set $U \times I$, the algorithm explores the maximum matching of the recommendation degree w of two-sided users, that is $w_{u,i} = arg\,max \sum_{u,i} f(u,i) \times g(i,u), \forall u \in U, i \in I$.

The algorithmic key to OMC service recommendation depends on a professional match between the needs of patients and the expertise of physicians (Ju and Zhang, 2021; Yuan and Deng, 2022; Vearrier et al., 2022). Through topic mining of medical records, the system extracts patients' disease conditions and personal preferences. Then from a large number of candidates, the system selects the physicians most suitable for a specific patient and lists the most appropriate recommendations. Despite that OMC recommendation could be seen as an application of expert recommendation systems, finding experts with similar expertise and professional experience by mining historical consultations for topic mining, traditional expert recommendation systems are mostly patient-oriented one-way matching processes ignoring physician motivations, preferences, and willingness. In addition, there is a general tendency for patients to prefer physicians who are affiliated with more highly rated hospitals and are known for their specialties (Wen et al., 2019). In this situation, this recommendation system aggravates the imbalance of medical resources, the overcrowding of popular physicians, and the uneven distribution of workloads among physicians. For e-service recommendations, a reasonable model should care for both users. It should consider not only the professional match between patients and physicians but also the wishes and preferences of both parties, as well as the workload of physicians and the interpretability of recommendations. Figure 3 illustrates the framework for an OMC service recommendation system, which consists of four main stages and seven steps. The first stage prepares the records of historical consultations, including texts, graphics, audio, and videos, and cleans, filters, and extracts preferences from both sides of users. The second stage mines multi-modal data, learning physician expertise and patient needs. The patients' inquiry texts can be used to extract their explicit needs and invisible preferences. To embed physician expertise in a knowledge graph network, a three-dimensional heterogeneous network of "physician-discipline-disease" is constructed from historical consultations. The prospect theory could be applied to explore physicians' invisible preferences based on their academic and professional experience. The third phase involves exploiting recommendation algorithms for medical professional matching. The final phase consists of validating the models with real-world data, testing their effectiveness and algorithmic performance efficiency, and adjusting the models or algorithms.

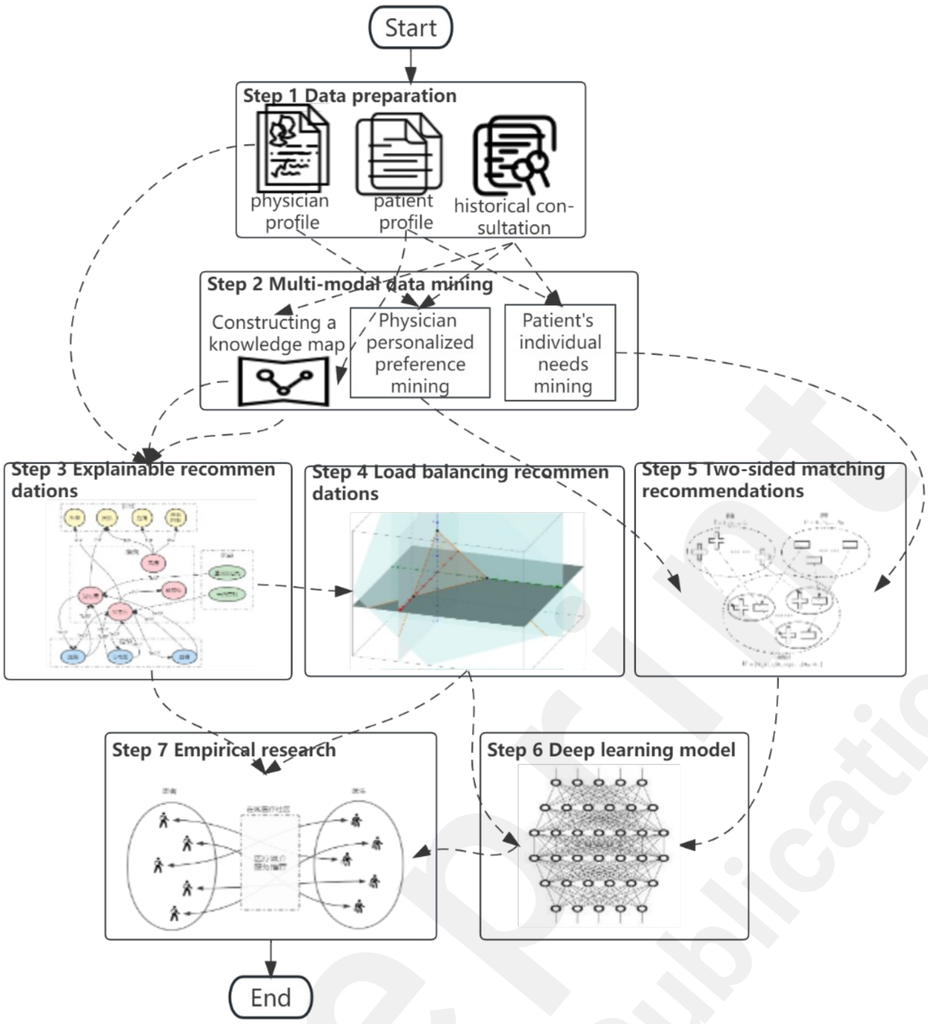

Figure 3: The OMC service recommendation algorithm framework diagram.

4. Data and features engineering

Research on recommendation systems begins with data engineering, and the data quality determines the quality of the recommendations. An accurate acquisition of features enables an effective recommendation system, and feature engineering forms the foundation of personalized recommendation systems.

4.1 Data acquisition

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 (Wang et al., 2017b; Ren and Ma, 2021). 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(Sadman et al., 2021). In addition, many studies collect primary data through questionnaires directed at patients or physicians(Waqar et al., 2019). Table 2 lists various data sources, including numerous OHCs and institutes.

Table 2: Comparison of various data sources

Literature	Data types	Sources

Ju & Zhang (2021)[38]	online	wy.guahao.com
Meng & Xiong(2021) [39]	online	chunyuyisheng.com
Sadman et al(2021) [34]	offline	Medical Specialty dataset of MT samples
Wang et al (2021)[33]	online / offline	HaoDF.com; disease-ontology; China Hospital Ranking, released by Hospital Management Institute of Fudan University
Yang et al (2020) [21]	online	HaoDF.com
Ye et al (2019)[12]	online	HaoDF.com; xywy.com

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. It is, however, one of the most fundamental works in recommendation system research.

Table 3: Basic components of OHCs' data sets

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

4.2 Data engineering

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(Ju and Zhang, 2021). 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(Yuan and Deng, 2022). 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 don’t 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 (Xu et al., 2019a), patients’ uncertain characteristics and preferences could be revealed by uncertainty languages, and fuzzy analysis could be used to improve recommender systems’ sparsity problem. Yuan and Deng (2022) introduced knowledge graphs to represent physician-patient interaction features in the physician recommendation problem, thereby alleviating data sparsity. Zaman and Li (2014) utilized a socio-semantic approach to address the problem of data sparsity caused by user-based collaborative filtering. Son and Choi (2020) used ordinal and binary ratings of experts to refine user opinions and mitigated data sparsity in hand-edited expert recommendations. Wang et al. (2020) proposed a matrix decomposition to handle sparse data and improve prediction accuracy.

4.3 Feature extraction

Medical science is a specialized field. 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, latent Dirichlet allocation (LDA), utilizes an unsupervised probabilistic model to generate topics(Tian et al., 2014; Ye et al., 2019). Typically, LDA is used to extract topics from large data sets of documents by mining potential semantic relationships between them. Xiong and Meng (2021) used all physician consultations as a corpus for LDA, as shown in Figure 4, and each physician receiving text-topic distribution was trained to retrieve the corresponding physician within a specific topic. Zhang et al. (2017b) applied LDA to extract patients' potential preferences and the characteristics of the physicians they consulted from patient reviews. LDA has some shortcomings. First, LDA lacks semantic contextual information when processing text, because the commonly used Bag of Words (BoW) model ignores it (Yan et al., 2020). 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. (2019) reduced the time complexity of LDA via Gibbs sampling and determined the optimal number of LDA topics based on the confusion level. Because the patient's "initial inquiry" text is usually short and the corresponding topic vector representation is sparse, Liu (2018) used a short text aggregation algorithm to represent the topic vector. Pan and Ni (2020) 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.

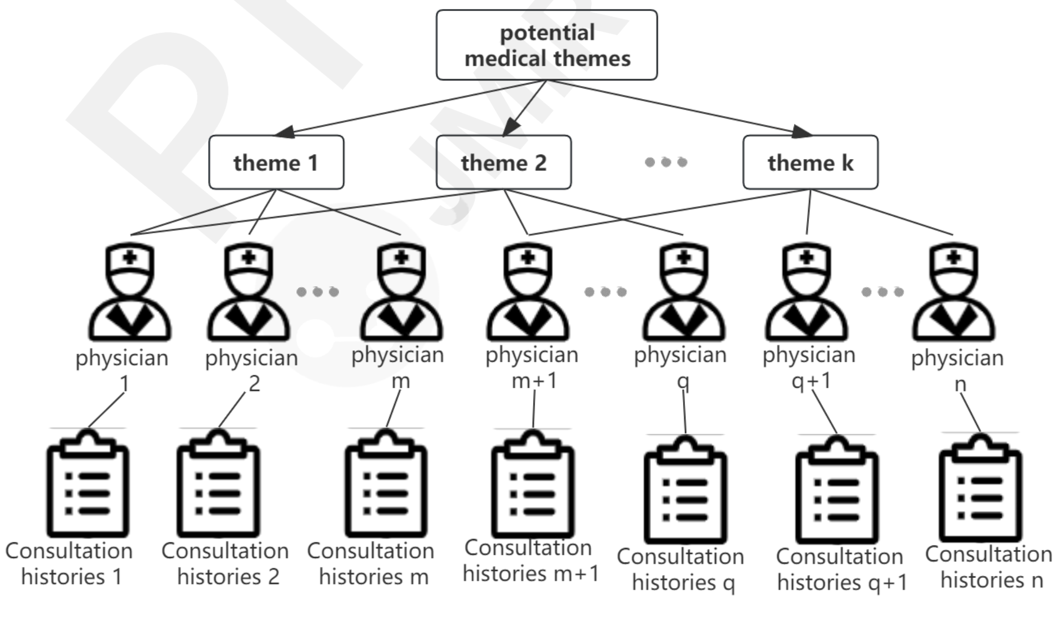

Figure 4: exploring physician potential medical themes.

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. Ye et al. (2019). 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. (2017b) used unsupervised learning methods to calculate the offset between patients' comments and their sentiments and correct the original patient ratings. 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. (2019) utilized the binary long-term short-term memory (Bi-LSTM) method, which achieved better results than sentiment dictionary analysis. For sentiment polarity analysis in review texts, Wu and Sun (2021) used the BERT model, and for recommendation results, they applied the Wilson interval method. 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(Xu et al., 2020). 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(Yuan et al., 2014). Yang et al. (2020) converted raw data into IFNs to describe uncertainty information by combining the patient's disease description with comments. Xu et al. (2020) examined data based on hesitant fuzzy language multi-criteria preference analysis to enhance patient preferences for physician recommendations.

4.4 Personalized preferences

Personalized recommendations are based on user preferences, and acquiring accurate user preferences is key to ensuring their quality(Yang et al., 2020; Pan et al., 2018). 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. (2020) proposed a two-sided recommendation framework for digital platforms to mitigate user emergence. The patient's personal preferences influence their selection behavior and thus their satisfaction with the recommendations(Wen et al., 2019; Waqar et al., 2019; Ju and Zhang, 2021). 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(Chen et al., 2020). 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.

4.4.1 Patient preferences

Patients' preferences and needs have been relatively adequately explored in existing studies on physician recommendations. As shown in Table 4, 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. (2018) proposed a user preference learning algorithm to learn patient preferences. Jiang and Xu (2014) 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. Jiaxin et al. (2020) employed SPSS to screen patient decision factors and recommend physicians based on their composite scores. Wang et al. (2020) even directly used the number of visits as an important determining factor for how patients viewed the standard of care provided by physicians. Xu et al. (2019a) investigated the privacy issues of patients and provided a multi-indicator group decision-ranking system of physicians.

Table 4: Factors influencing a patient's decision to choose a physician

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. (2014)	√	√	√	√	√	√	√		√					
Liu et al. (2016)		√	√		√									
Deng et al. (2019)			√			√		√						
Li et al. (2019a)				√	√	√		√						
Li et al. (2019b)		√	√		√			√						
Li&Hubner (2019)					√									
Xu et al. (2019a)				√		√			√					
Xu et al. (2019b)							√		√				√	
Gong et al. (2021)		√	√		√	√		√						√
Ju et al. (2021)					√				√	√				
Ta et al. (2021)						√								
Wang et al. (2021)			√				√	√	√			√		

Yuan et al. (2021)	√				√	√		√				√	
Li et al. (2022)		√		√	√								

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 (Wang et al., 2020). 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 (Deng et al., 2019). Generally, physician reputation can be divided into two categories: offline reputation and online reputation(Liu et al., 2016). 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. (2016) 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. Deng et al. (2019) also concluded that the title of the physician had a significant impact on the choice of the patient. 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. (2019b) demonstrated that hospital rank and physician professional credentials negatively moderate the effect of physician online ratings and activity on patient choice. Huang et al. (2021) revealed that a physician’s high title negatively moderates the effect on physician service ratings, while positively moderating the number of service reviews. Word-of-mouth in OHCs determines physicians’ online reputation(Deng et al., 2019; Huang et al., 2021). The experiences of previous patients, reviews, and recommendations are important decision sources for newcomers. Deng et al. (2019) revealed that the number of views and votes received on physicians’ homepages positively influenced patients’ choice of physician. Gong et al. (2021) examined the impact of online reviews and online ratings of physicians on patient decisions from the perspective of trust theory. A significant positive contribution to patient choice was also found in the study of Ta and Fu (2021) by the number of online reviews, while the proportion of negative reviews had a significant negative contribution to patient choice to a greater extent than the proportion of positive reviews. Li et al. (2019b) 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. Li and Hubner (2019) demonstrated that patients preferred physicians with higher technical skills over those with higher interpersonal skills based on the different dimensions of physician ratings.

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 (Guo et al., 2017; Huang et al., 2021). 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. (2019) 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. Gong et al. (2021) noted that updating physicians' information frequently and providing quality online services were critical to building trust between physicians and patients. Using the number of physician publications of popular articles in OHCs, Li et al. (2019b) found that physician activeness was positively associated with patient selection.

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 (Pan et al., 2018; Yang et al., 2020). 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 (2021) considered the location of the patient to improve the convenience of combining online consultation with offline treatment. Deveugele et al. (2002) 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. Compared to geographical location, consultation costs have relatively little impact on patients' choice of OMC services. Khairat et al. (2019) reported that costs were one of the primary factors determining patients' choice between mobile health and telemedicine. Fletcher et al. (2018) 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.

Others. The personal characteristics of a physician, such as his or her appearance and gender, can also influence patients' choices. Ouyang and Wang (2022) found that a serious and stable physician appearance image contributes to patients' trust in physicians, which in turn influences their medical choices. Additionally, patients have some stereotypes about physicians' genders. Li et al. (2019a) illustrated that patients generally perceive female physicians as having superior interpersonal skills. The gender difference in physicians also extends to the distinction between different departments and medical specialties. Bertakis (2009) found that male and female physicians practice in different ways, 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. (2021) found that physician gender influences physician ratings and patient choice, and that patient choice is enhanced when the physician is male.

4.4.2 Physician preferences

Continual physician involvement is crucial to the survival, growth, and prosperity of OHCs(Chen et al., 2020). 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(Liu et al., 2020b). 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(Guo et al., 2017). 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 5 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.

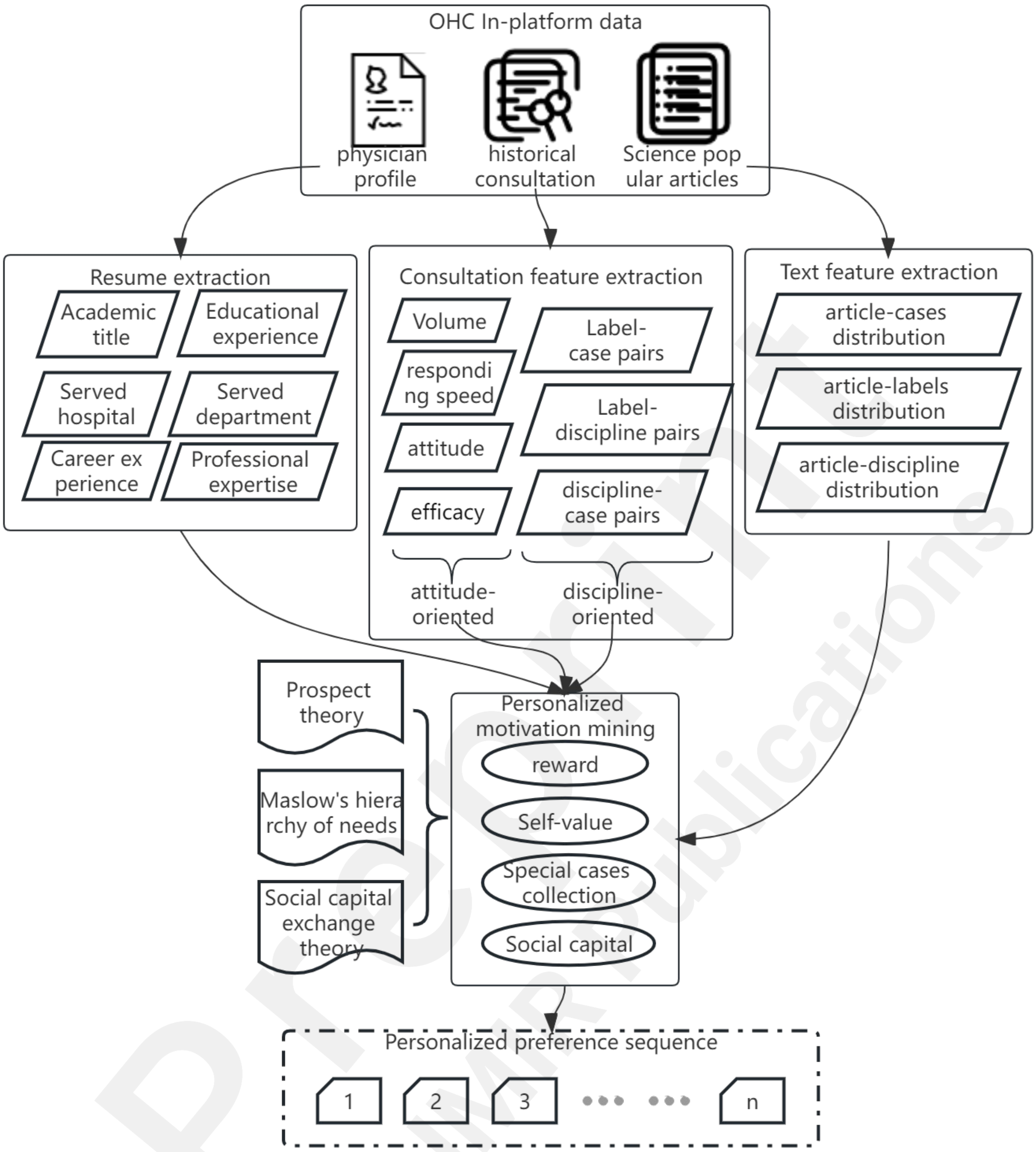

Figure 5: Physician personalized preference mining.

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(Chen et al., 2020; Zhang et al., 2017a). 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 physicians' willingness to do so. Using expectancy theory, Chen et al. (2020) 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. Zhou et al. (2019) 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. Yang et al. (2021) 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. Zhang et al. (2020b) found that when physicians reach an advanced level of expertise and knowledge, their material motivation declines and their professional motivation increases. Some physicians place great emphasis on personal branding, and their online services are designed to support their brand positioning and identity. Zhang et al. (2021) 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.

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 (2021) investigated the factors influencing physicians' economic income in OHCs in the context of the pandemic. 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 (Zhang et al., 2020b), 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. (2017a) reported that mutual aid and altruism can positively influence the willingness of health experts to share knowledge. In addition, reputation and self-efficacy can play a greater role in health experts' willingness to share knowledge than regular users. Yang et al. (2023) demonstrated that physicians are motivated to share paid messages for a variety of reasons. External motivation, enjoyment motivation, and professional motivation are all important factors.

Social rewards. According to the literature(Wang et al., 2017b), 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. (2020a) 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.

4.5 Privacy protection issues

National legislation to protect user privacy in the healthcare sector is among the most stringent(Xu et al., 2019a; Zhou et al., 2019). 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(Lu and Rui, 2018). Technically, collaborative filtering models are not suitable for OMC recommendation scenarios, regardless of whether they are based on userCF 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. (2019a) 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. Similarly, to ensure patient privacy, Narducci et al. (2015) constructed a semantic recommendation system that does not link the health data entered by patients to their true identities. 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.

5. E-service recommendation algorithm

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.

5.1 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. Li et al. (2009) proposed an expert recommendation method that combined fuzzy text classification and fuzzy pLSA text classification to build an expert knowledge model that was then based on time and other factors. Based on TF-IDF, STM, LDA, and semantic models, Riahi et al. (2012) examined expert recommendations within question-and-answer communities. Their experiments demonstrated that two topic models performed better than traditional information retrieval techniques. Pan and Ni (2020) modeled the textual topics of historical consultations and physician responses under each section, 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. (2015) utilized interactive links between scientific social networks and subjective and objective information features. Wang et al. (2017a) proposed a convolutional neural network for answering online expert questions, 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 6. Recently, expert recommendation research has increasingly incorporated integrated models that combine features such as social networks and knowledge content. Xu et al. (2012) 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. Yang et al. (2015) employed information about research relevance, personal social networks, and institutional connections to identify the most appropriate experts for collaboration on research. Xu et al. (2019b)proposed a methodology for a collaborative recommendation that integrates expert expertise and social information in a complex heterogeneous network utilizing heterogeneous network mining. 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(Nikzad-Khasmakhi et al., 2019). Both of these features are present in the OMC service recommendations studied in this study.

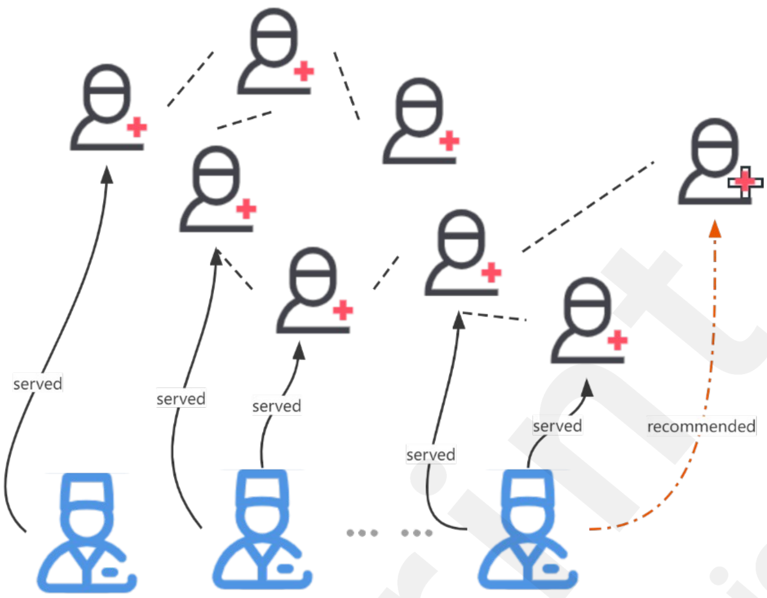

Figure 6: Social network-based recommendations.

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(Hur et al., 2021). 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 (2022) produced a more accurate and interpretable recommendation scheme based on the knowledge graph to overcome the problem of sparse data. 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 7, 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.

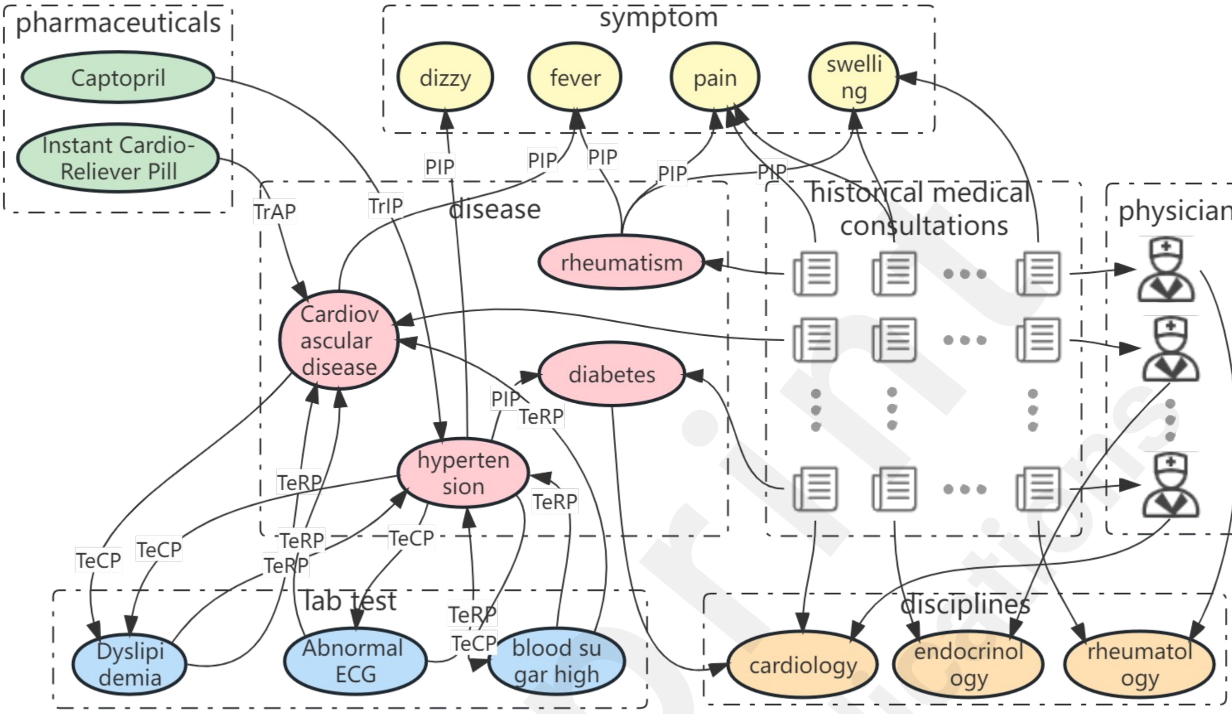

Figure 7: An example of data sampling to construct the physicians' knowledge graph.

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. (2017) constructed a knowledge graph, and from the parameter training, a disease-symptom topological relationship graph was generated. Liu (2018) used the K-means algorithm to cluster physicians and generalized goodness-of-fit metrics to evaluate and adjust the clustering results. 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. (2019b) 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. Based on the similarity of consultation texts, Xiong and Meng (2021) constructed a co-occurrence label network of physicians and calculated the centrality of the feature vector to recommend the most important physicians. Gong et al. (2015) 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. 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.

5.2 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 8. 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(Xi and Juan, 2018). For a one-to-many dual matching between surgical patients and physicians, Yuan and Jiang (2019) proposed a rational matching scheme based on physician preference for surgery, patient preference, and expectations for the physician. Patro et al. (2020) proposed a fair recommendation model for digital platforms on two-sided markets, which ensures that providers have not less than some dynamic threshold of exposure and that each customer is fairly treated. Xi and Juan (2018) 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. Gao et al. (2019) analyzed the problem of matching decisions for medical services in OHCs and constructed a matching decision model that is both satisfactory and stable. Zhong and Bai (2018) analyzed the patient-physician preference matrix and constructed a two-way matching model for specialty outpatient appointments oriented toward satisfying patients and physicians. Yang et al. (2019) used the two-sided matching theory to design a patient-specialist paired appointment system, in which the appointment process and the one-to-many appointment matching algorithm were described. Chen et al. (2019) developed an innovative multi-attribute decision-making method for two-sided matching, taking into account the psychological behaviors of matching bodies, as well as values of aspiration levels and evaluations.

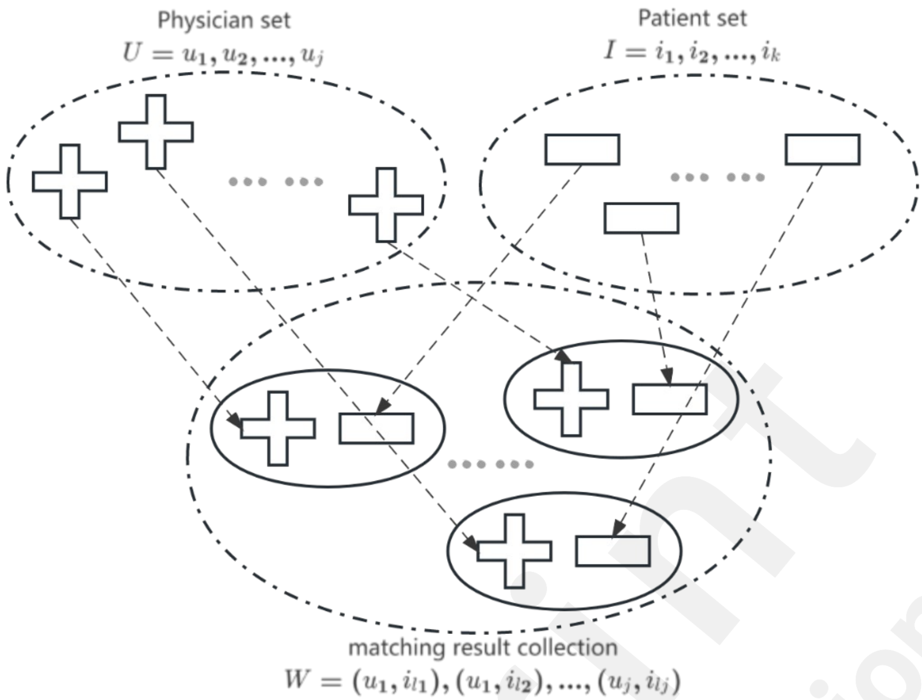

Figure 8: Physician-patient matching diagram.

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 9 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.

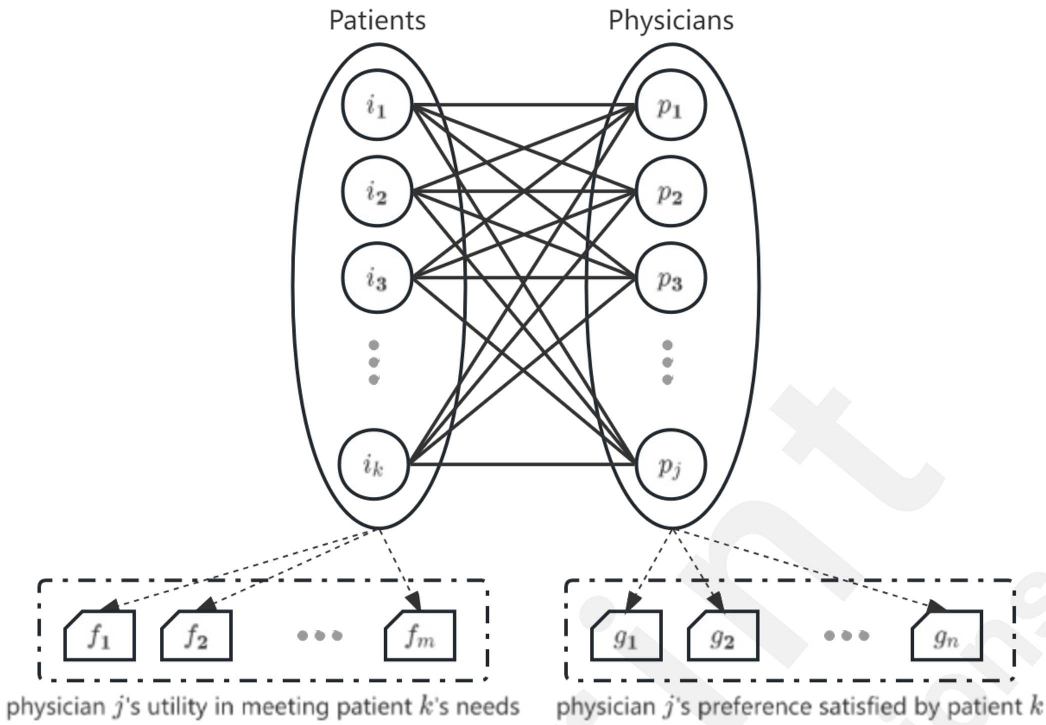

Figure 9: Modeling of physician-patient personalized preference order maximization.

5.3 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 (Wang et al., 2020). Physician overload affects physician fatigue and consultative quality, as well as patient waiting time, which deteriorates the comprehensive evaluation of the recommendation system(Pan et al., 2018). Currently, very few studies have explicitly considered the workload of recommended physicians in recommender systems. Based on the two-sided matching theory, Zhang and Zhao (2020) used data-driven statistical methods to provide the methodology for the two-sided matching of doctors and patients. To address the problem of unbalanced utilization among physicians, Pan et al. (2018) 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. To balance patient preferences and hospital staff workload, Wang et al. (2020) developed a 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. Yuan and Deng (2022) 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. In addition to reducing the workload of chief physicians, Yang et al. (2020) increased the number of recommendations to new physicians, which translates into a saving of time and money for patients. 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 and Kwon (2011) presented heuristic neighborhood techniques and matrix decomposition techniques to generate a more diverse set of recommendations with a lower workload for each physician. Pedronette and Torres (2012) proposed a method for reordering image content retrieval systems that combined recommendations with clustering and encoding context through ranking lists. Among the two-stage algorithms, Yu et al. (2019) investigated the relationship between recommendation accuracy and diversity and proposed an adaptive trust-aware recommendation model to improve cold-start and long-tail items. In the literature (Wen et al., 2019), 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. (2020) 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. 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.

5.4 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(Yuan and Deng, 2022). 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(Khedkar et al., 2020). 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(Yuan and Deng, 2022). 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 (2021) 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. To identify the different roles of physician-patient interaction characteristics and individual physician characteristics in physician recommendations, Yuan and Deng (2022) 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. 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 new 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.

6. Evaluation of service recommendations

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. (2016) 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. Ye et al. (2019) recruited 18 Ph.D. 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. Wu and Sun (2021) used a questionnaire to assess the accuracy of a physician's recommendation and validate the proposed recommendation algorithm, 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(Nikzad-Khasmakhi et al., 2019). 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(Yang et al., 2020), 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(Adomavicius and Kwon, 2011). 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.

7. Summary

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.

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Supplementary Files