Construction and Application of User Profiles in Online Healthcare Communities: Postprint

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Abstract

[Purpose/Significance] User profiles in online medical communities enable the concise extraction of patient needs and visual description of patient characteristics, assisting platform administrators in formulating more precise information service strategies.

[Method/Process] Based on a review of research findings on user profiles in online medical communities, this study proposes a framework for constructing such profiles. User data from diabetes communities on Baidu Tieba was crawled, and a combination of profile inventories, composite graphics, textual descriptions, and word cloud methods was employed to implement the construction of online medical community user profiles featuring four dimensions and twelve tags.

[Results/Conclusion] This theoretical framework and implementation method facilitate precise information recommendation, improve patient experience, and enhance decision-making quality, providing theoretical and practical guidance for the construction and application of user profiles in online medical communities.

Full Text

Preamble

Construction and Application of User Personas in Online Health Communities

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Abstract: [Purpose/Significance] User personas in online health communities (OHC-UP) can concisely extract patient needs and visually describe patient characteristics, helping platform managers formulate more precise information service strategies. [Method/Process] Based on a review of OHC-UP research, this paper proposes a construction framework for OHC-UP and crawls user data from the diabetes community on Baidu Tieba. Using a combination of file lists, composite graphics, language description, and word clouds, we construct OHC-UP with 4 dimensions and 12 tags. [Result/Conclusion] This theoretical framework and implementation method facilitate accurate information recommendation, improve patient experience, and enhance decision-making quality, providing theoretical and practical guidance for OHC-UP construction and application.

Keywords: user persona; online health community; diabetes
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Introduction

Under the "Internet Plus" initiative, online health communities (OHC) such as Ping An Good Doctor, Haodf.com, WeDoctor, and Chunyu Doctor have emerged, transferring traditional medical services to online environments and continuously reshaping diagnosis and treatment processes, including doctor-patient matching, doctor-patient communication, and personalized medical services. Achieving precise matching between doctors and patients, topics and patients, and health knowledge and patients can not only improve the quality and efficiency of information acquisition for users but also enhance the effectiveness of customized services provided by OHCs. Precise matching requires a foundation of finely detailed and clearly described user needs to enable appropriate recommendations of doctors, topics, and health knowledge. User persona (UP), as an emerging tool for user needs discovery, matching, and modeling, represents a key focus and hotspot in research on online health knowledge management and services [1].

UP is based on user-centered design (UCD) [2] and constitutes a visualized collection of tags that reconstruct attribute characteristics and provide scenario descriptions [3]. Leveraging the massive data aggregated by online health applications (such as web communities on PC and apps on mobile), refining user attributes and constructing user personas is a prerequisite for precise recommendation and services on online health platforms [1]. Research on user personas in Chinese online health communities ("User Persona in Online Health Community," abbreviated as "OHC-UP") is relatively scarce, with only 10 relevant papers besides review articles (citation database: CNKI; retrieval date: October 31, 2020). For example, Zhang Haitao et al. used the ConExp tool to convert user tags into concept lattices and classified user groups through Hasse diagrams of concept lattices to achieve group personas for health communities [4]. International research on OHC-UP is more extensive, particularly user personas centered on patient-centered design (PCD), which have become a research hotspot. Established PCD-based user personas include those for cardiovascular disease medication users [5], traditional medicinal plant users [6], and elderly people with chronic diseases [7]. Refined tags such as work, gender, age, IT experience, website search ability, physical characteristics, cognitive characteristics, work characteristics, lifestyle, social support, mobile usage, usage anxiety, and health information search have been successfully applied in patient personas [5,7-8]. Application scenarios for these patient personas include e-health preference judgment, visualized medical records, and personal health status assessment [5-8].

However, the above studies lack generality in their OHC-UP construction schemes, and interpretations of application methods in specific scenarios need further enrichment. Based on this, this paper comprehensively employs multiple tag expressions and persona generation methods to propose a more general OHC-UP construction framework, applies it in practice to enhance research implementation effectiveness and practical value, and clarifies what practical problems OHC-UP applications can solve, aiming to provide reference and guidance for improving knowledge services on online health platforms.

2 Framework for OHC-UP Construction

OHC is a network platform that provides medical information services to users. This paper primarily discusses OHC-UP oriented toward people who have or may have certain diseases. Drawing on existing literature [5-8], we propose a general OHC-UP construction framework whose core steps include tag system establishment, community data collection, and user persona presentation, as shown in [Figure 1: see original paper].

2.1 Tag System Establishment

The main purpose of establishing an OHC-UP tag system is to create a PCD-based restorative patient role, using segmented tags to mine the needs, desires, and obstacles of OHC patients. The basic principles of the PCD-based tag establishment process include: placing patient prototypes at the design center; prioritizing attention to patients and their tasks; ensuring usability. Based on these principles, this paper establishes the OHC-UP tag system top-down, including three stages: tag top-level design, tag refinement, and tag expression rules.

2.1.1 Tag Top-Level Design According to the principle of placing patient prototypes at the design center, tag top-level design needs to restore research objects from different, distinctive, and comprehensive perspectives. Unlike existing studies that focus only on certain aspects [4-8], this paper summarizes and integrates four core attributes of OHC users: Natural person attributes. These have definite demographic statistical characteristics and all needs naturally possessed by individuals [7-8]. Patient attributes. The target of information services is people who have or may have certain diseases, requiring functional service segmentation based on disease location, type, and corresponding department [6-7]. Online person attributes. OHC endows users with virtual roles and identities, allowing users to display online images distinct from their real-world identities [4]. Community person attributes. These involve the need to maintain group relationships, spontaneously generating attachment to community groups and establishing interpersonal bonds with other users [4], as shown in [Figure 2: see original paper].

2.1.2 Tag Refinement According to the principle of prioritizing patients and their tasks, selected tags should have PCD functions: providing help to users, conveying user needs, being used for task analysis, and being used for customer service. Based on this, this paper refines the sub-tags of the four core attributes mentioned above by referring to existing literature, as shown in .

(1) Natural person attributes. Name (or ID number) is the basic identifier of OHC users in the real world, used by community managers and other members to identify and confirm others' real identities [7]; age, gender, and residence are common standards for segmenting users based on demographic characteristics and can serve as basic reference for information push (such as hospital information, doctor information, daily care suggestions, etc.) [4]; occupation aims to describe how OHC users earn income in real life and what labor they need to perform, facilitating targeted information services from communities and medical staff [7-8]; desire is the most anticipated appeal of OHC users to real life, used by community managers or medical staff to provide core care [7].

(2) Patient attributes. Disease type is the most important tag for PCD designers to classify OHC users, used for functional differentiation of medical health information services [5,7-8]; disease duration and disease risk are basic bases for judging the urgency of physical (or psychological) health needs and are regarded as descriptions of OHC users' health status [7-8].

(3) Online person attributes. Nickname (or user ID) is the basic identifier of OHC users in virtual communities, used by community managers and other members to identify and confirm others' virtual identities [4]; information load is the amount of information users need to contact when participating in OHC, representing the time and energy OHC users are subjectively willing to invest in health information services [9]; information preference is the degree of preference for various types of health information in the community, used to support push systems in conducting precise information recommendations based on personal preferences [4,10].

(4) Community person attributes. Social type aims to characterize OHC users' social willingness, needs, and abilities, which can assist communities in deciding whether to push social information to users and how much information to push [10]; social emotion aims to identify what emotions users convey to other OHC members, whether positive, negative, or

neutral [11].

2.1.3 Tag Expression Rules According to the principle of ensuring usability, it is necessary to clarify the specific expression methods and expected results of OHC user tags in Table 1. Some tags are expressed using natural language description, directly extracting content from evidential text, as shown in . The expression rules for tags are explained below:

(1) Disease type. To obtain unified and standardized disease codes and names, the International Classification of Diseases (ICD) is imported into an Excel database [12] as a reference for fuzzy matching user descriptions of disease types in UGC.

(2) Disease risk. The severity of disease development determines the priority of patient treatment and disposal, such as triaging patients according to critical, severe, urgent, and non-urgent conditions, and grading them according to disease type as low-risk, medium-risk, high-risk, and very high-risk.

(3) Information preference. According to existing literature, key content can be extracted from community topics followed on user homepages, or high-frequency words can be extracted from user dialogue data to determine personal information preferences [4].

(4) Social type. Existing literature distinguishes social types based on the relative high or low in-degree and out-degree of OHC users' social networks, suggesting that if the distribution of in-degree and out-degree values conforms to a normal distribution, the 3σ principle should be used as the judgment basis; otherwise, the 80/20 rule should be adopted as the differentiation criterion [13]. This paper uses a social type matrix for network node in-degree/out-degree to divide user social types into four categories: expert type, aristocrat type, fan type, and Buddhist type, as shown in [Figure 3: see original paper].

(5) Social emotion. Naive Bayes is a widely adopted sentiment analysis method that trains sentiment classification models through corpora to judge the emotional states implied in patient community dialogues [14].

2.2 Community Data Collection

Community data collection is an intermediate step in the OHC-UP construction process. After completing the tag system establishment, OHC data needs to be extracted to support the UP tag expression process. Here, community data collection is subdivided into three stages: community data crawling, data cleaning and processing, and persona data preparation.

2.2.1 Community Data Crawling Unlike existing literature that advocates prioritizing data acquisition to mine features and extract tags [4-5], this paper advocates determining tags first and collecting data to express specific tags according to community manager needs. Community data needed to construct OHC-UP includes user homepage data, user dialogue data, user follow data, and user diagnosis and treatment data. For OHC managers, there is no need to crawl community data; they only need to retrieve it from the backend database of the service system. However, clarifying the descriptive content, application methods, and logical relationships between UP tags for the above data is still beneficial, as shown in .

2.2.2 Data Cleaning and Processing OHC data cleaning and processing specifically include [13]: removing invalid values; merging duplicate items; data standardization; key content extraction. After the above data processing work, data is stored in an appropriate database (such as SQL Server) to form a preliminary dataset.

2.2.3 Persona Data Preparation To form a persona dataset, it is also necessary to eliminate low-quality data containing NULL values or low credibility from the preliminary dataset according to actual research conditions, ensuring that any tag of OHC-UP has corresponding and credible supporting data. The reasons are as follows: incomplete data directly limits the tag expression process, resulting in "incomplete" personas in the final results; existing research has found that personal information filled in by users and online comments they generate may be inconsistent with facts [15]. Therefore, constructing OHC-UP with incomplete data or low-credibility data will reduce the decision-support capability of personas and the decision-making quality of community managers. Thus, the persona data used in this paper is essentially a high-quality dataset with reduced scale and improved credibility, filtered from big data to meet the appropriate granularity pursued by researchers.

2.3 User Persona Presentation

The essence of OHC-UP generation is to use the prepared dataset to calculate the tag expression results of patient prototypes category by category and item by item according to the tag categories, items, and expression rules in the established tag system, assign tag information, and after completing all calculations and "filling" all tags, establish the final result in a visualized, application-friendly, or even innovative persona to provide reference for OHC managers or medical staff.

This paper constructs OHC-UP with 4 dimensions and 14 tags, of which 8 tags use natural language description, 2 tags use rating scales, and 4 tags use type range description. The underlying supporting technologies for this persona include data mining, social network analysis, and sentiment analysis. The presentation methods comprehensively adopt four approaches: the cutting-edge theory and widely used file list, composite graphics, language description, and word cloud.

3 Application of OHC-UP

Following the constructed OHC-UP framework and the theoretical steps in Section 2, this paper conducts an empirical test using Baidu Tieba to generate user personas for the diabetes community, further illustrating the feasibility and application value of this theoretical framework.

3.1 Tag Selection

Based on the data characteristics of users in the diabetes community on Baidu Tieba, the general OHC-UP tag system in Section 2.1 is revised: the name tag is deleted due to research ethics restrictions as privacy consent cannot be obtained from subjects; the occupation tag is deleted due to data collection limitations as occupation is not a required field for Tieba users.

Ultimately, 12 tags are selected: nickname, age, gender, residence, desire, disease type, disease duration, disease risk, information load, information preference, social type, and social emotion. Combined with the specific community characteristics of the diabetes forum, the tag expression rules are revised as follows: residence is inferred as the location of the treatment hospital; disease duration is inferred as the time of the diagnostic report; disease risk refers to patient descriptions, laboratory indicators, and auxiliary reports; when desire lacks evidential text, automatic summarization is used as a proxy variable [16]; average active duration is used as a proxy variable for information load (average active duration is the ratio of post count to forum age), with information load divided into 5 levels at 0.20 intervals.

3.2 Data Collection

This paper uses Python to write crawler code to crawl user homepage data and posting data from participants in the "Diabetes Bar" topic forum on Baidu Tieba in 2020. The diabetes forum on Baidu Tieba was selected for research for the following reasons: it has a large-scale user base as research subjects [9]; it has accumulated rich patient-generated content and interaction data [9]; publicly available diagnostic material images from patients can be obtained; diabetes is listed among China's top ten high-incidence diseases [17]; user information behavior data is dynamic and time-sensitive [11].

Homepage data can obtain participants' forum age, post count, follow posts, follow lists, and follower lists, used to calculate three tags: information load, information preference, and social type, as shown in [Figure 4: see original paper]. Posting data includes comment text (dialogue data) and diagnostic images (diagnosis and treatment data). Comment text serves as direct evidence, generates automatic summaries, or provides corpora for sentiment analysis, used to calculate three tags: nickname, desire, and social emotion, as shown in [Figure 5: see original paper]. Diagnostic images are used to identify and extract key content to calculate six tags: age, gender, residence, disease type, disease duration, and disease risk, as shown in [Figure 6: see original paper].

After further processing the above data according to the methods in Sections 2.2.2 and 2.2.3, a persona dataset containing 85 data entries is formed, as shown in [Figure 7: see original paper].

Here, necessary explanations are provided for the tag anchors of disease type, information load, and social type: this paper is the first to introduce internationally 通用的 disease coding categories into OHC-UP research. Diabetes (E10-E14) includes five categories: insulin-dependent type, non-insulin-dependent type, malnutrition-related type, other specified type, and unspecified type [12]. Operational criteria include age, body type, ketoacidosis, insulin treatment effect, other indicators, and disease reports. Therefore, although this paper uses diabetes community users as the data source, subjects' disease types are not completely homogeneous. Among them, E10 is insulin-dependent diabetes, E11 is non-insulin-dependent diabetes, E12 is malnutrition-related diabetes, E13 is other specified diabetes, and E14 is unspecified diabetes.

Based on the persona data, the information load indicators of all users are calculated in descending order to determine anchors: Guaguapi Da* (Order=17, post count=2817, forum age=6.5), Po Nickname Zhen Nan* (Order=34, post count=1197, forum age=8.6), Wang Laoshi Wo Mei* (Order=51, post count=196, forum age=4), Qing Yi Bai* (Order=68, post count=124, forum age=7.9), and Qing Jiao Wo Liu Zong* (Order=85, post count=3, forum age=6.7). The intervals for angel, loyal, regular, tourist, and zombie users are determined as $(+\infty, 433.38]$, $(433.38, 139.19]$, $(139.19, 49.00]$, $(49.00, 15.70]$, and $(15.70, 0.00]$, respectively.

According to the division method required by the literature, the social type intervals for users in this paper are calculated [13]. When $F(x \leq x_0) < 0.8$, x_0 is selected as the boundary line to determine the in-degree anchor as Dikanong* (in-degree=116, F(x\$ 116) $< 0.8) and De Ji * (in - degree = 119, F(x\ 119) < 0.2), and the out - degree anchor as De Ji * (out - degree = 43, F(x\ 43) < 0.8) and fyudlts007 * (out - degree = 44, F(x$ \$44)<0.2). The results show that in-degree>116 and out-degree>43 is expert type, in-degree>116 and out-degree<44 is aristocrat type, in-degree<119 and out-degree>43 is fan type, and in-degree<119 and out-degree<44 is Buddhist type.

3.3 Persona Presentation

This paper creates a model instance of OHC-UP application design, providing an information system for encoding and identifying user configurations and role attributes. Due to space limitations, only two examples are reported, as shown in [Figure 8: see original paper] and [Figure 9: see original paper]. Unlike existing OHC-UP literature that adopts tags and presentation designs [10,20], this paper supplements the influence of the public's internal psychological forces and external social forces on healthcare choices and outcomes [24]. This expands the role references not previously designed in traditional character profiles and individual attributes, including: Desire, which reflects PCD's core care for stakeholders through sentence-based text generation summarization [16]; Disease/diabetes detection and diagnosis, which extracts disease type and condition information from medical reports provided by patients and specifies disease/diabetes types using ICD codes; Information services, which grasp and rank users' limited interests and concerns through word frequency statistics; Social support networks, which construct patient networks through social network analysis of homepage follow data to clarify the differentiated social needs of different patients.

In the OHC-UP application process, visualization technology enhances the presentation effect of patient prototypes and role characteristics. The overall design adopts the file list advocated by C. Lerouge et al. [7], which scholars believe is a widely accepted tool for capturing, designing, and developing enhanced character tools for user features in the context of public healthcare technology popularization. The impression design uses composite graphics advocated by V. Haldane et al. [5], presenting important tags such as OHC users' social types through graphic combinations that suit readers' cognitive structures, are easy to understand and infer, quickly capture key features and details, and facilitate short-term memory formation. Language description and word clouds supplement conventional design. Language description is the most direct information feedback method in UP presentation modes, using straightforward and most persuasive ways to display condensed key features and evidential text [7], while word clouds can better reflect the thematic scope and ranking of users' information preferences [3].

Compared with existing studies [3-5], this paper expands persona tags to 12 items and generation methods to 4 types. The good presentation effect of this OHC-UP also benefits from the high-quality persona dataset. Existing decision theory indicates that when decision conditions are numerous and complex, decision-makers may not necessarily make optimal decisions even with more effort [11]. To some extent, personas based on this paper's data have stronger decision-support capabilities due to their relatively moderate granularity and complexity. Expanding the persona dataset to the original dataset does not affect the implementation of this OHC-UP application design but only results in instances containing blank tags in the generated results.

4 Results Analysis and Implications

The successful implementation and promotion of OHC-UP largely depend on the cognition of community service providers [7,18]. This means that for patients to successfully develop dependence on communities and their information services, developers must recognize that the key to adopting OHC-UP is the acceptance of both service providers and service recipients—that is, OHC-UP adoption should have application value, and patients should be willing to allow developers to use this technology to provide information services [7]. Therefore, this paper combines the generated OHC-UP instances to explain in detail how OHC-UP scenario applications can meet community practice needs for accurate information recommendation, improved patient experience, and enhanced decision-making quality.

4.1 Accurate Information Recommendation

In the two OHC-UP instances, "Ru Qin Ruo Huo*" is a low-risk malnutrition-related diabetes patient with high information load level (angel user), while "Shengxing*" is a high-risk insulin-dependent diabetes patient with medium information load level (regular user). If recommending reference medical information and professional health knowledge to these users: in terms of information type and content, the former should focus on other diseases causing diabetes and be advised to seek nearby medical treatment, while the latter is more suitable for learning about effective blood sugar reduction, diet control, and exercise plans, and should be considered for early treatment at authoritative medical systems; in terms of information volume and frequency, the former is more suitable for high-volume and high-frequency push services, while the latter may become tired of excessive information and push notifications.

Compared with existing persona literature's recommendation models [4-5], this paper provides richer tags (disease type, disease risk, information load, etc.) to serve accurate information recommendation. From an information perspective, OHC information services are required to provide more personalized attention, and the use of technical tools helps save their limited resources (such as time) [7,9,11]. This OHC-UP, as an information system, can efficiently present users' necessary personalized attention and feedback through its output user file list. Similarly, this also clarifies how OHC-UP can and should serve as an important tool for community managers to provide accurate information services for patients.

4.2 Improved Patient Experience

In the two OHC-UP instances, "Ru Qin Ruo Huo*" is a young male who enjoys socializing and shows low mood, accompanied by diseases such as gout, anxiety disorder, and AIDS. The community should recommend interesting information about raising pet birds, treatment cases of other patients successfully fighting diseases, etc., to guide him to develop beneficial interactive relationships with optimistic community members. "Shengxing*" is a middle-aged male who is indifferent to socializing and emotionally neutral, but a fan of hiking, planting, poetry, and collecting. Community services should amplify his hiking interests and promptly notify him about offline activities such as recent exhibitions on plants, poetry, and collecting, to maximize the patient's exercise needs and external social needs as much as possible.

Compared with existing persona literature's service concepts [4-5], this paper pays more attention to humanistic care for patients, especially the social and emotional status of patients of different genders, age groups, and complications. From the patient perspective, patients are not actually lacking resources for diabetes awareness and knowledge [7], but rather find it difficult to encounter concentrated and interesting signals and opportunities beneficial for regulating physical and mental health and specific diseases. That is, patients can access various other information sources, but the relative quality and reliability of these sources need verification [15,19], and the discovered signals and opportunities are basically irrelevant to their own diseases. Therefore, besides users' natural person and patient attributes, this OHC-UP also focuses on online person and community person attributes, providing patients with information services that are not directly related to but beneficial for their diseases through multi-dimensional attribute fusion and associated feature mining, activating their social-driven interests and health behaviors.

4.3 Enhanced Decision-Making Quality

In the two OHC-UP instances, the two users' desires differ significantly. "Ru Qin Ruo Huo*" states the huge psychological distress caused by disease to his personal mental state, while "Shengxing*" expresses his yearning for a healthy diet and warnings about unhealthy diets. In fact, community managers can infer users' deep psychological characteristics based on their desires [7]. Therefore, the former actually desires more positive externalities from OHC services (such as encouragement, comfort, and frequent interaction), while the latter seems committed to improving diet plans but essentially aims to expand and activate personal interests (such as appreciation of poetry, vine plants, strange stones, and meteorites).

Compared with existing persona literature's decision-making thinking [4-5], this paper differs in its community operation decisions based on patient psychology and behavior feature mining and user habit determinism. Personal preferences have certain complexity [3,9], and managers may develop more than one one-sided misconception based on this consideration. Service strategies considering personal preferences are sometimes not effective. Only by "walking in their shoes" (a metaphor used by Western scholars) and truly designing for users can conflicts in decision-making teams be resolved [7]. This OHC-UP, based on fully capturing user features, attaches importance to users' desired core care, helping decision-makers develop exchangeable cognition of users' mental states.

Conclusion

In theoretical terms, this paper extracts an OHC-UP construction framework, explaining the underlying logic and implementation mechanism of the OHC-UP construction process from three core steps: tag system establishment, community data collection, and user persona presentation, and refines specific, general, and replicable operational stages. This theoretical framework provides theoretical basis and methodological guidance for OHC-UP construction and application. In practical terms, this paper crawls user data from the diabetes community on Baidu Tieba, comprehensively uses file lists, composite graphics, language description, and word clouds to implement OHC-UP with 4 dimensions and 12 tags, and discusses the feasibility and application value of this OHC-UP construction framework and implementation method, as well as what scenarios it can be applied to and what problems it can solve.

The following aspects are valuable for addressing this paper's limitations: OHC service targets are people with health information needs, mostly with patients as core customers and traffic sources [9,19]. This paper has good applicability and application value for the above communities but is not suitable for OHCs with doctors as core customers. Future research should conduct UP studies for more niche online doctor communities. The empirical part fails to address concerns from scholars such as A.J. McLeod and J.G. Clark that actual OHC operating system users may differ from presumed primary users [20], and situations where family members, public welfare personnel, etc., may generate community content (such as posts, diagnostic images) on behalf of patients may exist, requiring researchers to provide suitable identification technologies and algorithms. Future research should refine the ICD coding of disease type tags, expanding to four- and five-digit codes for subcategories and subdivisions of disease categories [12] to provide more targeted diagnosis, treatment, and healthcare services.

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Author Contributions:

Teng Chun'e: Proposed the research plan, wrote the paper, processed and analyzed data;
He Chunyu: Designed the research framework, proposed revision suggestions, revised the paper.

Note: Figure translations are in progress. See original paper for figures.