Postprint: Research on Health Information User Switching Behavior Based on LDA Model Factor Extraction

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Abstract

[Purpose/Significance] The development of mobile health information services can generate substantial potential value for the healthcare industry; however, its overall adoption lags behind sectors such as financial services, attributable to numerous influencing factors inherent in the transfer process. Text mining of research findings on user health information behavior can effectively uncover latent primary influencing factors, thereby elucidating their impact on transfer behavior.

[Method/Process] Employing LDA model-based text analysis and integrating social identity theory, this study conceptualizes relative perceived value and relative loyalty as key influencing factors, with transfer cost as a moderating factor, to construct a research model of user transfer behavior determinants and conducts empirical validation.

[Results/Conclusion] Findings indicate that LDA model analysis yields relatively specific feature words, through which effective influencing factors can be extracted. Moreover, these factors demonstrate high theoretical congruence, and the model grounded in social identity theory and related factor theories exhibits strong explanatory power for user transfer behavior.

Full Text

A Research on User Transfer Behavior in Health Information Based on LDA Model Factor Extraction

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Abstract

[**Purpose/Significance**] The development of mobile health information services can create tremendous potential value for the medical industry, yet its overall adoption lags behind sectors such as financial services due to numerous influencing factors during the transfer process. Text mining of research findings on user health information behavior can effectively reveal the primary underlying factors and summarize their impact on transfer behavior. [**Method/Process**] This study employs the LDA model for text analysis, combined with social identity theory, to construct and empirically analyze a research model of user transfer behavior with relative perceived value and relative loyalty as key influencing factors, and transfer cost as a moderating factor. [**Result/Conclusion**] The results demonstrate that LDA model analysis can extract relatively specific feature words, through which effective influencing factors can be obtained. These factors show high consistency with actual theory, and the model proposed based on social identity theory and related factor theories exhibits good explanatory power for user transfer behavior.

Keywords: health information service; LDA model; factor exploration; user transfer behavior

1. Introduction

In an era of continuous social and economic development with improving living standards, people are increasingly willing to devote time to pursuing better lives. However, as life accelerates, time has become a scarce resource. Health information services represent important means for improving quality of life. When time spent on health consultations encroaches upon other activities, new personal and social costs emerge. To reduce these costs, people attempt to construct new information service models.

Since the 21st century, information technology has continuously evolved, the information society has gradually matured, and mobile information services have developed rapidly. With technological advancements, mobile device performance has improved, mobile internet quality has been enhanced, and numerous applications have entered the mobile domain, extending services to all aspects of users' lives. Against this backdrop of ubiquitous mobile services, integrating health services with mobile technology has become essential. Supported by mobile devices and networks, mobile health information services (MHIS) have emerged as a new method for providing health information. MHIS enables access to health information resources through mobile technology, allowing users to obtain healthcare consultation services anytime and anywhere. This approach overcomes geographical, temporal, and organizational barriers at low cost, alleviating tension between health service supply and demand while optimizing health service delivery [1].

In China, the health industry has begun adopting mobile information technology, but the number of users who actually choose MHIS remains small, with most adopting a wait-and-see attitude. Currently, two groups exist: those using traditional health information services (THIS) and those using MHIS. Users accepting traditional services face the choice of whether to transfer to mobile services, similar to previous transitions from offline to online retail and from branch banking to online banking. Social identity theory posits that individuals develop identification with their group through social categorization, generating in-group preference and out-group bias [2]. When confronted with the new MHIS user group, this group consciousness strongly influences attitudes and behaviors within the traditional group, interfering with health information acquisition methods and affecting transfer behavior. This transfer behavior lies between initial adoption and continued use; only through initial adoption can users be attracted to continued usage. Therefore, this research addresses two questions: (1) What factors primarily influence user health information adoption behavior in current research? (2) Do potential relationships exist among these factors that may further influence transfer behavior? Consequently, this study conducts latent topic exploration through the LDA model to identify factors influencing user health information service adoption, examines potential relationships among factors, and uses social identity theory as the theoretical foundation to propose relative perceived value and relative loyalty as factors influencing user transfer behavior. It also explores the moderating effect of transfer cost and establishes a model to demonstrate the internal mechanisms of inter-group user transfer behavior, thereby expanding research on this phenomenon.

2. Related Theoretical Foundations

2.1 Characteristic Elements of Mobile Health Information Services

The constituent elements of mobile health information services differ from traditional services, primarily including five components: service subject, service object, service target, service platform, and information service strategy [3]. The service subject refers to personnel providing mobile health information services, generally from the traditional service group, who demonstrate capability through attributes such as workplace, education, and professional title. The service object refers to health information output during the mobile service process, which originates from the service subject and is transmitted via mobile communication technology as video, audio, images, and text, rather than through face-to-face interaction. The service target refers to users of mobile health information services—primarily mobile service users who recognize security and usefulness and are willing to use MHIS to partially replace traditional services. The service platform serves as the channel for transmitting the service object between subject and target, providing technical support and management to ensure successful service completion. The information service strategy and approach is the method determined jointly by the service subject and platform, providing reliable means for effective mobile information services.

2.2 Transfer Behavior In the current environment where information technology is ubiquitous, research must focus not only on user adoption intention but also on promoting user transfer to MHIS. P. Song et al. [4] defined usage transfer behavior as users continuing to use a technology product while simultaneously adopting another that meets new needs. C. Ye et al. [5] argued that attention should be paid to users' "post-adoption" behavior and studied factors influencing switching between alternative technology products. Their findings showed that user satisfaction and breadth of use of existing products were negatively correlated with transfer behavior, while perceived ease of use, relative advantage, and perceived security of alternative products were positively correlated. L. Fei et al. [6] believed that post-adoption transfer behavior exists and used "uses and gratifications theory" to identify factors motivating user transfer, finding that perceived relative value of new services positively influenced transfer intention. C. Calvo-Porral and J.P. Lévy-Mangin [7] studied factors influencing satisfaction and loyalty generation among users under transfer costs between traditional network services and virtual mobile services. Chen Minghong et al. [8] constructed a two-dimensional transfer behavior framework, examining factors influencing user transfer from PC search to mobile search. Dai Bao and Deng Aiwen [9] analyzed factors influencing social media user transfer behavior from push, pull, and anchoring levels. Xu Xiaojuan et al. [10] studied user transfer drivers from traditional paper media to digital media through structured interviews.

In both traditional and mobile health information services, users face the choice of whether to transfer usage, a decision influenced by various factors. Exploring the most likely influencing factors and clarifying their mechanisms of action is significant for studying user health information service transfer behavior.

3. Exploratory Analysis of Factors in User Health Information Behavior

3.1 Topic Model A topic model is a language model where topics can be viewed as probability distributions of terms, while documents are mixtures of multiple topic probabilities. It transforms documents from term space to topic space, obtaining document representation in low-dimensional space [11]. Based on topic models, useful semantic information can be extracted by identifying unique topics or concepts in text for research tasks such as distributed semantics, word sense induction, or information retrieval. Topic models have evolved through stages including Latent Semantic Analysis (LSA), Non-negative Matrix Factorization (NMF), to Latent Dirichlet Allocation (LDA) [12].

The LDA model is a probability model based on a three-layer Bayesian structure of document-topic-term [12]. The model assumes article writing follows this pattern: selecting certain topics related to current content with a certain probability, then selecting terms these topics may contain with a certain probability, and repeating these steps to generate a coherent article. The LDA model reverses this process, assuming that document topics in the corpus can be represented as probability distributions. By analyzing documents to extract

their topic probability distributions, topic clustering or text classification can be performed, aiming to infer relevant topics from a given corpus and topic distribution from a given document.

Current topic analysis primarily uses the LDA model and its derivatives. Extensive research has been conducted in computer science [13-14], biomedicine [15-16], journalism and communication [17-18], and user behavior research [19-20]. Additionally, academic literature mining has received considerable attention. K. Lee et al. [21] constructed a topic-method network based on LDA analysis, integrating topic model and network analysis to understand research dynamics in communication studies. Guan Peng and Wang Yuefen [22] combined the LDA topic model with life cycle theory to study multi-period, multi-level topic clustering and evolution throughout disciplinary life cycles, using new energy literature for experiments. Results showed good topic extraction effects that could provide predictions for research hotspots and trends. Wang Yuefen et al. [23] used the LDA topic model to explore disciplinary knowledge structure and hotspots, using CNKI database to deeply analyze and identify numerous hotspot topics across multiple disciplines. Wang Wenjuan and Ma Jianxia [24] used LDA to conduct topic analysis on ocean acidification literature, exploring correlations between theme intensity changes in NSF-funded projects and actual research papers. Results showed LDA could effectively identify research topics. Shang Xianli [25] analyzed potential interdisciplinary topics in digital libraries through LDA, obtaining research hotspots in interdisciplinary fields.

This study is based on literature mining, further analyzing and establishing an influencing factor model oriented toward mobile health information service topics, and exploring the possibility of combining topic models with structural equation models, which has innovative significance for health information behavior research.

3.2 Data Acquisition According to the research theme, this study focuses on user information service transfer behavior in the mobile health context, using CNKI as the literature source database and employing self-programmed crawler technology to collect target literature.

The specific search strategy was: limiting the search type to "theme" ; limiting the search object keyword to "user" ; limiting the domain keyword to "health, information" ; limiting the scope keyword to "influencing factors" ; limiting the collection content to "abstract" ; with no restrictions on literature type or search time. Ultimately, 1,229 entries were retrieved, with 1,199 valid data points collected.

3.3 Data Preprocessing The corpus data was saved in CSV format. Data was read, cleaned, preprocessed, and analyzed using Python in Pycharm. Preprocessing included tokenization and stop-word removal, establishing a corpus to form a document-term matrix, and performing TF-IDF weighting.

In LDA model establishment, pre-determining the number of topics is important for increasing accuracy. Two main approaches exist: (1) Exhaustive method (empirical method). An initial number of topics is set based on experience, then continuously enumerated to compare model effects and select a suitable number. This method is simple and yields topic words conforming to general cognition, but cannot prove optimality. (2) Perplexity method. Perplexity evaluates model representation ability—lower perplexity indicates stronger representation. However, more topics often result in lower perplexity in LDA models. To avoid overfitting, LDA proposer D.M. Blei et al. used perplexity-topic number curves to measure representation ability, using the inflection point where the curve flattens as the appropriate topic number [12]. This method provides strong theoretical basis but cannot guarantee topic words meet expectations.

Given that this study conducts exploratory analysis without setting expected results according to general cognition, the perplexity method was chosen. The perplexity-topic number curve is shown in Figure 1 [Figure 1: see original paper]. As the number of topics increases, perplexity decreases rapidly and flattens when the topic number reaches 7, thus determining the topic number as 7.

3.4 Data Results The corpus and topic number were input into the LDA model to obtain topic-word distributions and the proportion of documents containing each topic. The top 30 words by probability were selected as feature words for each topic. Generally, each topic contains numerous feature words, making direct analysis difficult. For instance, this study' s results include many feature words not directly related to influencing factors. Therefore, the top 9 words with the strongest representation for influencing factors were selected as the actual factors explored. Simultaneously, labels were added to topics based on feature words to obtain clearer connotations. Through the topic-word distribution table, 7 topic labels were extracted using manual labeling, designing expressions that summarize most feature words through expert discussion, ultimately forming topic labels.

Specifically, words such as "medical," "community," "interaction," and "sharing" were semantically condensed into "health information interaction" ; words like "health," "information," "perception," "evaluation," "risk," and "quality" became "health information quality" ; words such as "informatization," "disease," "wearable," "algorithm," and "care" represent "health information technology" ; while words like "remote,""trustworthy,""prevention,""monitoring,""reliable,"and "credibility" represent requirements for health information technology; words such as "emotional," "sensitive," and "urgent" became "user emotion" ; and words like "recommendation," "intention," "mutual assistance" demonstrate "recommendation intention" ; words such as "fast," "stable," "effective," "price," "maximization," and "integrity" represent "cost-performance ratio." As shown in Table 1 :

Table 1 Topic-Word Distribution

Topic	Label	Proportion	Feature Words
1	Health Information Interaction	10.1%	Community, Interaction, Sharing, Demand, Adoption, Socialization, Clustering, Social, Medical
2	Health Information Quality	7.4%	Health, Information, Perception, Evaluation, Risk, Quality, Disease, Chronic Disease, Nursing
3	Health Information Technology	7.4%	Informatization, Wearable, Algorithm, Technology, Remote, Monitoring, Prevention, Reliable, Credibility
4	Health Information Technology Require-ments	7.4%	Stable, Trustworthy, Requirement, Information, Quality, Technology, Service, System, Standard
5	User Emotion	7.4%	Emotion, Sensitivity, Urgency, Perception, Experience, Attitude, Satisfaction, Trust, Preference
6	Recommendation Intention	2.5%	Recommendation, Intention, Mutual Assistance, Sharing, Word-of-mouth, Trust, Attitude, Satisfaction, Experience
7	Cost-Performance Ratio	2.5%	Price, Cost, Efficiency, Maximization, Integrity, Standard, Quality, Service, Value

3.5 Results Analysis This study explores potential influencing factors and analyzes relationships among them, requiring further examination of connections between topics. Analysis of the topic-word distribution table reveals varying correlations between different topics. For instance, the concept of social groups appears in most potential topics (words like "community," "social," "socialization," "clustering") and in over 80% of documents. Based on this finding, we hypothesize that potential influencing factors in the form of topic labels have certain connections, providing a foundation for subsequent condensation

of specific factors and research on relationships among them.

According to LDA model analysis results, the concept of "social group" occupies a relatively large proportion. Theoretical analysis was conducted using the core idea of social group transfer in social identity theory. Social identity theory suggests that individuals are aware of belonging to specific social groups, and group membership provides value and emotional significance. In social identity formation, individuals develop relatively high identification with high-value groups, generating positive evaluations and exhibiting behaviors such as pride and loyalty [26]. In the health information service domain, social identity theory is well manifested. The traditional group, after long-term use of traditional health information service acquisition methods, recognizes its value and develops loyalty. To transfer users' health information acquisition methods, users need to develop relatively higher perceived value of MHIS to generate loyalty to this service.

User perceived value in health information services refers to patients' overall evaluation of health information utility after weighing perceived benefits and losses, representing an extension of customer perceived value theory [27]. J.C. Sweeney and G.N. Soutar [28] argued that perceived value should include cost value, quality value, emotional value, and social value. In the mobile health domain, Hu Rong et al. [27] classified perceived value into functional value, emotional value, efficiency value, and social value, studying the formation mechanism of patient perceived value. Zhao Wenjun et al. [29] studied the impact of social value, information value, and emotional value on users' intention to continuously use social platforms. These studies show that perceived value classifications have application value in health information and largely overlap with this study' s LDA model analysis results, which can be regarded as specific factor representations of cost-performance ratio (cost value, efficiency value), health information quality (quality value, functional value, information value), user emotion (emotional value), and health information interaction (social value), verifying the assumption of potential relationships among topics.

User loyalty is generally divided into behavioral loyalty and attitudinal loyalty. Behavioral loyalty focuses on actual user behavior, measured by repetition frequency, while attitudinal loyalty focuses on user attitude, measured by repurchase intention and recommendation intention [30]. In health information services, the frequency of service purchases is difficult to control and is in uncertain flux. In dynamic environments, attitudinal loyalty can better identify user value [31]. Meanwhile, certain characteristics of traditional domains become competitive advantages. For instance, in THIS, non-verbal information from face-to-face communication provides psychological comfort amplified [32], thereby increasing user loyalty and making users tend to identify with the traditional group. The LDA model analysis shows that usage intention (words like "demand," "adoption" in Topic 1, "wearable" in Topic 3, and Topic 4' s focus on "requirements") and recommendation intention (words like "interaction," "sharing" in Topic 1, and "recommendation," "mutual assistance" in Topic 6)

are conceptually similar to attitudinal loyalty, again demonstrating correlation among topics.

Therefore, based on social identity theory and combined with LDA model analysis results, this study focuses on the influence of relative perceived value and relative loyalty in inter-group user transfer behavior, and examines the moderating effect of transfer cost.

4. Research Model Development and Analysis

4.1 Factors and Hypotheses

4.1.1 Relative Perceived Value S.K. Lam et al. [33] proposed relative perceived value, defining it as the degree to which a product' s functional benefits exceed those of an alternative within the same category. This study defines relative perceived value as the degree to which MHIS user-perceived value exceeds that of traditional methods. Based on previous research and literature mining results, four types of relative perceived value are proposed:

(1) **Relative Time Cost Value**. There is significant correlation between time cost value and functional value [34]. In user health information acquisition, assuming no significant difference in service levels, MHIS' s most significant group advantage over THIS is time savings. Therefore, this study proposes relative time cost value to enhance contrast between the two methods.

(2) **Relative Quality Value**. Quality value is an important component of functional value, derived from user expectations of product quality and service [35]. Due to differences in information acquisition methods, MHIS and THIS may generate different user perceptions regarding information quality and professionalism. As the primary recognition method for health information, relative comparison of quality should be a major factor influencing group flow [35].

(3) **Relative Emotional Value**. Emotional value comes from feelings or emotional states generated by products [28]. Different usage experiences with MHIS and THIS affect users' emotional identification. Better experiences lead to higher emotional feedback recognition. Higher relative emotional value of mobile health information services facilitates user transfer.

(4) **Relative Social Value**. As part of perceived value, social value describes a product' s ability to enhance users' social attributes [28]. Users' choices are influenced by their social environment. When a health information acquisition method can better enhance users' sense of social belonging and improve social identity, that method has higher social value. As a new channel, higher relative social value in MHIS facilitates user identification.

4.1.2 Relative Loyalty S.K. Lam et al. [33] proposed relative brand identification based on loyalty to describe emphasis between brands. This study directly uses the relative loyalty concept, defining it as the degree of emphasis between MHIS and THIS. MHIS, as a new group, promotes user group flow by obtaining higher relative loyalty. This study combines the attitudinal loyalty concept, using relative usage intention and relative recommendation intention as measurement indicators:

(1) **Relative Usage Intention**. In attitudinal loyalty, "repurchase intention" refers to users' intention to repeat purchase behavior [36]. Repeatedly purchasing MHIS is essentially continuous use of information services. Users more inclined to continuously use a service represent higher usage intention and greater willingness to join that service' s user group. This study uses usage intention to replace purchase intention, defining relative usage intention as the degree of emphasis on using MHIS versus THIS in the future.

(2) **Relative Recommendation Intention**. Recommendation intention refers to users' willingness to recommend products to friends and acquaintances [36]. When group members recommend recognized services to other groups, it promotes group expansion and attracts members from other groups to transfer. This study defines relative recommendation intention as the degree of emphasis on recommending MHIS versus THIS to surrounding group members.

4.1.3 Relationship Between Relative Perceived Value and Relative Loyalty Social identity theory suggests that when facing social identity threats, group members enhance value identification with their group to consolidate loyalty (for example, the traditional group may enhance self-identification by increasing the value of face-to-face communication). D.J. Flint et al. [37] believed that user perceived value changes dynamically over time, significantly impacting loyalty maintenance. C.Y. Wang and L.W. Wu [38] found that user perceived value significantly impacts loyalty in long-term relationships. Users have developed usage habits and loyalty toward THIS. As a new service, MHIS needs to provide higher value to enhance loyalty. K.H. Wathne et al. [39] believed that excellent perceived value increases user exit barriers, passively enhancing loyalty. Users who receive good health information services from THIS perceive good value, which increases transfer barriers. D. Sirdeshmukh et al. [40] proposed that perceived value is the foundation for establishing loyalty in transfer relationships. Good perceived value increases loyalty. K.M. Chu and C. Shiu [41] proposed that if service providers can respond to users' various needs, it improves perceived value and thereby increases loyalty. Li Wu [42] divided perceived value into social value, price value, content value, interaction value, and interface design value, examining their impact on user loyalty to e-book reading clients. This study introduces the relative concept for degree comparison. Relative perceived value and relative loyalty are consistent

with perceived value and loyalty in basic concepts, so their relationship inherits the relationship between perceived value and loyalty. The level of relative perceived value generated by MHIS will affect users' relative loyalty. Based on this foundation, the following hypotheses are proposed:

H1: Relative time cost value positively influences relative usage intention.
H2: Relative time cost value positively influences relative recommendation intention.
H3: Relative quality value positively influences relative usage intention.
H4: Relative quality value positively influences relative recommendation intention.
H5: Relative emotional value positively influences relative usage intention.
H6: Relative emotional value positively influences relative recommendation intention.
H7: Relative social value positively influences relative usage intention.
H8: Relative social value positively influences relative recommendation intention.

4.1.4 Relative Loyalty and User Transfer Behavior Personal and identity identification is a complex but enduring memory structure [43]. Users who have long used THIS have formed identity identification, making it difficult to separate from the traditional group based solely on obtained value, thus tending to remain in the original group. Under social identity theory, this inherent identity relationship makes users less receptive to new services. However, the impact of new groups cannot be ignored. Users in the original group will, driven by social creativity, enhance the positivity of self-evaluation to weaken intention to transfer to new methods [44]. Users who have long used and recognized THIS are more willing to stay in the traditional group and abandon trying MHIS. Therefore, MHIS needs to enhance user loyalty to promote transfer behavior. Meanwhile, social identity theory suggests that users can have multiple identities, but the most recognized identity significantly influences choice behavior. Users with high loyalty consider their current identity more salient, and this salient identity prompts recommendation behaviors consistent with their identity [43]. Higher relative recommendation intention toward MHIS facilitates transfer to MHIS. Under identity identification, inseparability from usage methods, and social creativity, users tend to prefer THIS in continuous comparison. Therefore, enhancing relative loyalty to MHIS is important for achieving health information service method transfer.

In summary, relative loyalty impacts users' health information acquisition method transfer behavior. The following hypotheses are proposed:

H9: Relative usage intention positively influences user health information service method transfer behavior.
H10: Relative recommendation intention positively influences user health information service method transfer behavior.

4.1.5 Moderating Effect of Transfer Cost Transfer cost refers to the one-time transaction cost incurred when consumers switch from one product or service provider to another [45]. Users definitely incur transfer costs when transferring from THIS to MHIS. LDA model data analysis also shows that "price" and "cost" are potential factors. Therefore, this study introduces transfer cost as a moderating variable. S.K. Lam et al. [33] proposed that loyalty may be influenced by functional value and transfer cost. Shang Lin [46] found that user recommendation intention is affected by cost. Wang Desheng and Wang Jianjin [47] considered transfer cost important in brand transfer behavior. Therefore, the moderating effect of transfer cost during transfer from THIS to MHIS should be given attention. T.A. Burnham et al. [45] proposed that when users transfer between products or services, they are simultaneously influenced by procedural and financial transfer costs. This study' s subjects already have the material and capability foundation for using mobile information services, making financial transfer cost relatively minimal. Therefore, transfer cost is defined as procedural transfer cost, referring mainly to time and effort expenditure generated when transferring to MHIS.

In summary, this study proposes:

H11a: Transfer cost negatively moderates the relationship between relative usage intention and user transfer behavior.
H11b: Transfer cost negatively moderates the relationship between relative recommendation intention and user transfer behavior.

The research model is shown in Figure 2 [Figure 2: see original paper], with factor definitions provided in Table 2 .

Table 2 Definitions of Relevant Factors

Factor	Definition	Source
Relative Time Cost Value	The degree to which MHIS' s relative time expenditure is superior to THIS	J.C. Sweeney, G.N. Soutar [28]; S.K. Lam, et al. [33]; M.G. Gallaarza, I.G. Saura [34]
Relative Quality Value	The degree to which MHIS users' service quality and expectations substitute THIS	J.C. Sweeney, G.N. Soutar [28]; S.K. Lam, et al. [33]
Relative Emotional Value	The degree to which feelings or emotional states generated by MHIS substitute THIS	J.C. Sweeney, G.N. Soutar [28]; S.K. Lam, et al. [33]
Relative Social Value	The degree to which MHIS enhances users' social self-concept compared to THIS	J.C. Sweeney, G.N. Soutar [28]; S.K. Lam, et al. [33]; M.G. Gallaarza, I.G. Saura [34]

Factor	Definition	Source
Relative Usage Intention	The degree of emphasis user groups place on using MHIS versus THIS in the future	S.K. Lam, et al. [33]; J.W. Kim, et al. [36]; C.Y. Wang, L.W. Wu [38]
Relative Recommendation Intention	The degree of emphasis user groups place on recommending MHIS versus THIS to surrounding group members	S.K. Lam, et al. [33]; J.W. Kim, et al. [36]
User Transfer Behavior	The behavior of user groups transferring from THIS to MHIS	L. Fei, B. Xiao [6]; Wang Desheng, Wang Jianjin [47]
Transfer Cost	The time and effort expenditure generated by users when transferring to MHIS	S.K. Lam, et al. [33]; T.A. Burnham, J.K. Frels, V. Mahajan [45]

4.2 Research Design

4.2.1 Research Subjects In general terms, any natural person is a potential patient. Therefore, this study did not specifically select patients seeking medical treatment but chose users who use mobile services or have some understanding of them. Consequently, mobile service users were selected as the research sample. According to the "China Internet Network Development Status Statistical Report," as of June 2018, China' s mobile internet user population reached 788 million, accounting for 98.3% of all internet users. Therefore, this study distributed electronic questionnaires through mobile devices to ensure respondents have a foundation in mobile service usage.

4.2.2 Questionnaire Design As shown in Figure 2, the model includes concepts such as relative perceived value, relative loyalty, transfer cost, and user transfer behavior. Based on previous research, specific operational variables and measurement items for each concept were proposed, as shown in Table 3 . This study borrowed validated mature scales, distributed initial questionnaires to several graduate students and ordinary mobile service users to adjust item wording, then distributed and collected 50 questionnaires through mobile service channels. Based on data analysis results, items were adjusted again to improve the questionnaire. A total of 248 questionnaires were collected, with 20 unqualified questionnaires removed, resulting in 228 valid questionnaires (92% valid response rate). The sample covered various education levels and age groups, as shown in Table 4 .

Table 3 Operational Items and Sources for Each Factor

Factor	Item	Measurement Item	Source
Relative Time Cost Value	RTCV1	The planning and preparation time for adopting mobile health information services is lower than traditional service methods	J.C. Sweeney, G.N. Soutar [28]; M.G. Gallaarza, I.G. Saura [34]
	RTCV2	The transportation time for adopting mobile health information services is lower than traditional service methods	
	RTCV3	The time loss from adopting mobile health information services is lower than traditional service methods	
Relative Quality Value	RQV1	Mobile health information services may provide more reliable services	J.C. Sweeney, G.N. Soutar [28]; J.J. Cronin et al. [35]
	RQV2	Mobile health information services may provide more qualified service personnel	
	RQV3	Mobile health information service personnel may better understand my situation	
	RQV4	Mobile health information services may better meet my health needs	
	RQV5	Mobile health information services may provide more comprehensive health information	
Relative Emotional Value	REV1	Mobile health information services are my preferred service method	J.C. Sweeney, G.N. Soutar [28]
	REV2	Mobile health information services make me want to use health information services more	
	REV3	Using mobile health information services makes me feel more relaxed	

Factor	Item	Measurement Item	Source
	REV4	Using mobile health information services makes me feel more comfortable	
Relative Social Value	RSV1	Using mobile health information services may earn me higher social recognition	J.C. Sweeney, G.N. Soutar [28]; M.G. Gallaarza, I.G. Saura [34]
	RSV2	Using mobile health information services may represent personal level and standard	
	RSV3	Compared to traditional health information services, mobile services have been used more by people around me	
	RSV4	Mobile health information services may be more recognized by people around me	
Relative Usage Intention	RUI1	If I need to use health information services, I may prefer to use mobile health information services first	S.K. Lam, et al. [33]; J.W. Kim, et al. [36]; C.Y. Wang, L.W. Wu [38]
	RUI2	In the future, I may tend to continuously use mobile health information services	
Relative Recommendation Intention	RRI1	I may be more willing to introduce the advantages of mobile health information services to friends	S.K. Lam, et al. [33]; J.W. Kim, et al. [36]
	RRI2	I may prioritize recommending mobile health information services to those seeking my advice	
	RRI3	I may encourage people around me to try mobile health information services more	

Factor	Item	Measurement Item	Source
Transfer Cost	TC1	If I transfer to mobile health information services, I have to learn relevant usage knowledge from scratch	S.K. Lam, et al. [33]; T.A. Burnham, J.K. Frels, V. Mahajan [45]
	TC2	If I transfer to mobile health information services, I will spend too much time adapting	
	TC3	Transferring health information acquisition methods may be very difficult for me	
User Transfer Behavior	UTB1	After understanding or using mobile health information services, I tend to use other health information services	L. Fei, B. Xiao [6]; Wang Desheng, Wang Jianjin [47]
	UTB2	After understanding or using mobile health information services, I may choose to use it	
	UTB3	After understanding or using mobile health information services, I don' t want to have any connection with it	

Table 4 Descriptive Statistics of Questionnaire Sample

Characteristic	Category	Frequency	Percentage (%)
Gender	Male	128	56.14
	Female	100	43.86
Age	Under 18	2	0.88
	18-30	134	58.77
	31-45	62	27.19
	46-60	32	14.04
	Over 60	0	0
Education	High school or below	7	3.07
	Junior college	23	10.09
	Bachelor' s degree	119	52.19
	Master' s degree or above	79	34.65

4.3 Data Analysis and Hypothesis Testing

4.3.1 Reliability and Validity Analysis This study used SmartPLS software for data analysis. Factor loadings of all observed variables are shown in Table 5 , ranging from 0.73 to 0.90, all greater than 0.7, indicating explanatory power and significant impact on research variables. For reliability, Cronbach' s alpha coefficient and composite reliability (CR) tested internal consistency. When Cronbach' s alpha ≥ 0.70 and CR ≥ 0.70, data has good reliability. As shown in Table 5, Cronbach' s alpha ranges from 0.72 to 0.87, and CR values range from 0.84 to 0.91, reaching recommended levels and confirming statistical internal consistency and stability. Average variance extracted (AVE) ranges from 0.63 to 0.80, higher than the recommended 0.5, indicating good convergent validity. Additionally, as shown in Table 6 , the square root of AVE for each variable is greater than its correlation with other variables, indicating good discriminant validity.

Table 5 Reliability Analysis of Research Constructs

Factor	Item	Factor Loading	Cronbach' s α	CR	AVE
Relative Time Cost Value	RTCV1	0.77	0.87	0.90	0.68
	RTCV2	0.87			
	RTCV3	0.64			
Relative Quality Value	RQV1	0.82	0.88	0.91	0.64
	RQV2	0.88			
	RQV3	0.64			
	RQV4	0.81			
	RQV5	0.88			
Relative Emotional Value	REV1	0.64	0.79	0.87	0.69
	REV2	0.72			
	REV3	0.84			
	REV4	0.63			
Relative Social Value	RSV1	0.75	0.86	0.90	0.67
	RSV2	0.86			
	RSV3	0.67			
	RSV4	0.72			
Relative Usage Intention	RUI1	0.84	0.89	0.93	0.80
	RUI2	0.90			
Relative Recommendation Intention	RRI1	0.86	0.84	0.90	0.70
	RRI2	0.79			
	RRI3	0.87			
Transfer Cost	TC1	0.73	0.72	0.84	0.63
	TC2	0.86			
	TC3	0.81			
User Transfer Behavior	UTB1	0.88	0.85	0.90	0.70
	UTB2	0.89			
	UTB3	0.64			

Table 6 Square Root of AVE and Correlation Matrix of Latent Variables

	1	2	3	4	5	6	7
1. Relative Time Cost Value	0.83						
2. Relative Quality Value	0.45	0.80					
3. Relative Emotional Value	0.38	0.52	0.83				
4. Relative Social Value	0.41	0.48	0.56	0.82			
5. Relative Usage Intention	0.39	0.51	0.58	0.61	0.89		
6. Relative Recommendation Intention	0.42	0.49	0.55	0.59	0.67	0.84	
7. User Transfer Behavior	0.31	0.44	0.48	0.52	0.58	0.54	0.84

4.3.2 Model Hypothesis Testing Using SmartPLS software, model hypothesis testing results are shown in Table 7 . Among main effect hypotheses H1-H10, except H2 and H6 which are not supported, the other eight are supported. In the influence of relative perceived value on relative loyalty, relative usage intention is significantly positively affected by relative perceived value; relative

recommendation intention is significantly positively affected by relative quality value and relative social value, while relative time cost value and relative emotional value do not significantly affect relative recommendation intention. User transfer behavior is significantly positively affected by relative loyalty.

Regarding the moderating effect of transfer cost, it significantly moderates the relationship between relative usage intention and user transfer behavior but does not significantly moderate the relationship between relative recommendation intention and user transfer behavior. The moderating coefficient shows that transfer cost negatively moderates the relationship between relative usage intention and user transfer behavior. That is, users with low transfer cost are more likely to follow their relative usage intention and transfer to MHIS, consistent with hypothesis H11a. However, the relationship between relative recommendation intention and user transfer behavior is not moderated by transfer cost; regardless of transfer cost level, it does not affect users' compliance with relative recommendation intention, which does not match hypothesis H11b.

Based on empirical testing results, the revised model is shown in Figure 3 [Figure 3: see original paper].

To further understand the moderating effect, this study divided samples into high and low transfer cost groups based on mean plus/minus one standard deviation. Figure 4 [Figure 4: see original paper] shows this moderating effect pattern. As shown, users with low transfer cost demonstrate more significant impact of usage intention on transfer behavior compared to users with high transfer cost.

5. Conclusions and Future Directions

5.1 Discussion and Analysis With rapid development of mobile information technology, the mobile health domain will inevitably receive attention. How to make users accustomed to traditional health information acquisition methods willing to transfer to new methods has become the primary problem MHIS development must solve. This study first conducted exploratory data analysis through the LDA topic model, discovering and extracting factors influencing user health information service adoption. It then combined social identity theory to discuss potential influencing factors for transfer behavior, summarizing them with the two-dimensional concepts of relative perceived value and relative loyalty. Using 228 mobile service users as subjects, the study confirmed that the proposed model has good explanatory power, reaching the following conclusions:

(1) Data was obtained from CNKI using web crawler technology. During crawling, except for force majeure factors such as network failures and device limitations, the process was stable and efficient. The collected dataset was complete and usable except for inherent missing information, reducing data cleaning difficulty. The process proved the feasibility and stability of using crawler technology for literature collection.

(2) In LDA model topic analysis, data preprocessing was smooth, parameter selection was reasonable and effective, and results were authentic and usable. Through further analysis and organization, potential influencing factors were obtained, and these factors could be effectively combined with theory to explain relationships after analysis, demonstrating the feasibility of using topic models to explore potential factors and relationships.

(3) Except for individual relationships that are not statistically significant, other main effects between relative perceived value and relative loyalty are consistent with hypotheses. Transfer cost has a negative moderating effect on user transfer behavior, significantly moderating the relationship between relative usage intention and transfer behavior, but not significantly moderating the relationship between relative recommendation intention and transfer behavior. Although all hypotheses have theoretical or empirical support, considering domain differences, it is acceptable that some hypotheses are not supported.

(4) This study built a model based on literature mining combined with social identity theory. Perceived value and loyalty are often used as single variables to explain user behavior, but previous research found both can be more finely classified, and this classification aligns with data analysis results. This study adopted this classification to specifically explain user transfer behavior and achieved good explanatory effects. Consequently, reasonably refining influencing factors has practical significance and feasibility for in-depth problem analysis and should be emphasized in future research.

(5) Transfer cost is one factor influencing user transfer behavior. Data analysis also shows that "price" and "cost" are potential factors. This study introduced it as a moderating variable. Results show that transfer cost does not affect users' compliance with relative recommendation intention, which does not match the hypothesis. In actual situations, users recommending MHIS mainly transmits good usage experience as information to other group users without generating much procedural cost. Therefore, it is understandable that transfer cost has no significant moderating effect between relative recommendation intention and user transfer behavior.

The model received good feedback in empirical testing, proving that combining text data analysis with structural equation model research has practical significance and plays a realistic role in studying user transfer behavior, contributing to mobile health information field development.

5.2 Managerial Implications With rapid development of global mobile information services, users increasingly adopt mobile information services. Regarding the current situation of mobile health information services, how to promote user transfer to MHIS has become a problem requiring solution. Based on research conclusions, some reference countermeasures can be provided for

MHIS development:

(1) Users' relative perceived value significantly affects their relative loyalty, and relative loyalty significantly affects transfer behavior. From the perspective of user perceived value, MHIS can focus on relative time cost value and relative quality value. By providing health information services comparable to traditional methods while shortening acquisition time —such as online expert appointment consultation and online prescription acquisition—users' desire to further use MHIS can be stimulated. From perspectives of relative emotional value and relative social value, more convenient acquisition channels can be provided, simplifying operation procedures, optimizing user experience, enhancing adaptability to MHIS methods, while actively promoting MHIS into communities to serve the masses, allowing mobile information technology to truly serve the public and gain more social recognition. From the perspective of user loyalty, the transfer process is affected by loyalty to original services, which weakens transfer intention. Therefore, when introducing MHIS, attention should be paid to technology connectivity. For example, many hospitals currently use self-service registration and guidance systems, which are good transitional methods for interfacing with mobile information technology, allowing users to accept new methods subtly and generating social flow, thereby enhancing intention to use and recommend MHIS.

(2) Attention should be paid to certain user characteristics. Some users generate high transfer costs during group transfer, which may stem from discomfort with new things, spending much time learning new information technology, or encountering technical difficulties when using MHIS. These issues require MHIS to optimize and enhance user-friendliness to lower usage thresholds, and require providers to conduct popularization work, such as introducing how to use mobile information service platforms during guidance processes and helping users learn self-service. These methods, if continued long-term, will promote new group formation and diffuse social identity outward, influencing more people to transfer health information service methods.

5.3 Research Limitations and Future Directions Although this study strives for model reliability and rigorous verification, some limitations remain: (1) This study mainly discusses user transfer behavior, extracting influencing factors from previous research based on the LDA model, and building a new model supported by social identity theory. However, it cannot be determined whether it can comprehensively measure user health information service transfer behavior. Future research should innovate and hypothesize influencing factors. (2) Based on data analysis and empirical studies, transfer cost was selected as a moderating variable. Results show the negative moderating effect on the relationship between relative recommendation intention and user transfer behavior is not significant. Therefore, other moderating variables that may affect results

should be considered, hoping future research can try other moderating variables to make studies more meaningful. (3) Although questionnaires were distributed through mobile devices, due to limitations of time, manpower, and material resources, more samples could not be obtained for more detailed analysis. Future research should collect more samples to make studies more robust.

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