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ORIGINAL RESEARCH

Exploring the Health Literacy Behavior Patterns of Male Patients Using an Interpretable Method

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Background: Improving overall and individual health literacy is a major focus of national initiatives in China and similar initiatives globally. However, few studies have examined the identification and improvement of individual health literacy levels, especially among patients.

Purpose: To develop an interpretable method with decision rules to assess the health literacy levels of male patients and identify key factors influencing health literacy levels.

Methods: Using a convenience sampling method, we conducted on-site surveys with 212 male patients of a hospital in China from July 2020 to September 2020. The questionnaire was developed by the Ministry of Health of the People's Republic of China. A total of 206 of the completed surveys were ultimately included for analyses in this study. The rough set theory was used to identify conditional attributes (ie, key factors) and decision attributes (ie, levels of health literacy) and to establish decision rules between them. These rules specifically describe how different combinations of conditional attributes can affect health literacy levels among men.

Results: Basic knowledge, concepts, and health skills are important in identifying whether male patients have health literacy. Health skills, scientific health concepts, healthy lifestyles and behaviors, infectious disease prevention and control literacy, basic medical literacy, and health information literacy can be identified as cognitive behaviors with varying degrees of health literacy among patients.

Conclusion: This model can effectively identify the key factors and decision rules for male patients' health literacy. Simultaneously, it can be applied to clinical nursing practice, making it easier for hospitals to guide male patients to improve their health literacy.

Keywords: health literacy, male patients, key factors, decision rules, rough set theory, RST

Introduction

Health literacy (HL) has emerged as a focal point in global public health.[1] The concept was initially proposed around 1970, with subsequent active research on related measurement tools and interventions.[2] HL encompasses individuals' ability to effectively access, comprehend, and utilize health information and services, as well as how organizations can equitably promote and support individuals in health-related decision-making and actions.[3] Promoting best practices in HL has been shown to effectively enhance health equity, ensuring more people have access to necessary health information and services.[4] In contemporary society, there exists a correlation between individuals' HL levels and their health outcomes.[5] Individuals with higher HL typically demonstrate better health behaviors, while lower HL is closely associated with adverse health outcomes such as increased mortality rates, higher hospitalization rates, and other negative health-related consequences.[6–8] Therefore, improving HL is essential for fostering better health behaviors and ultimately contributes significantly to the enhancement of public health.

Since 2000, China has realized the importance of HL in regard to citizens' health. In 2008, the Ministry of Health of the People's Republic of China released an official document on Chinese citizens' basic knowledge and skills (for trial

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implementation) for the first time.[9] In 2015, the document was revised and incorporated into the nation's health development plan.[10] Since then, HL has been popularized nationwide and has become an important indicator of citizens' health levels.[11] In 2016, the State Council of China set the goal for residents' HL levels to reach 20% in 2020 and 30% in 2030.[12] According to the "Three-Year Action Plan for Enhancing HL of the Whole Population (2024–2027)" released by the National Health Commission,[13] new goals have been established to achieve an average annual increase of about 2 percentage points in the residents' HL levels and to promote this plan across cities nationwide. Therefore, improving HL is not only key to achieving these goals but also critical to the development of China's public health system.[14]

Furthermore, scholars have extensively studied the HL of residents in various cities such as Beijing,[15] Henan,[16] Guangdong,[17] Jiangsu,[11] and Shanghai.[18] However, these studies primarily focus on urban residents, with insufficient attention given to assessing the HL of patients. Patients are a crucial group facing health challenges, and identifying and improving their HL is vital for improving their health outcomes.[19]

Lower levels of HL have been shown to lead to poor health outcomes.[5] Differences in HL levels result from a combination of factors. Appropriately identifying and intervening in these key factors can enhance HL.[16] Therefore, it is imperative to identify these key factors influencing HL and understand the hierarchy of health risks individuals may face under specific conditions, enabling targeted interventions to improve HL levels. However, reliable and objective quantitative methods are needed to assess this information. Currently, research on HL primarily employs statistical methods.[18,20,21] However, these methods often assume that variables are independent,[22] which does not effectively reflect the interrelationships among them.

In contrast, data mining techniques excel at uncovering correlations and nonlinear relationships within datasets,[22] particularly gaining widespread recognition in addressing multifactorial issues in medical decision-making[23,24] and risk assessment.[25,26] Among these techniques, rough set theory (RST) is an effective data mining method for handling multifactorial problems.[27–29] Unlike other black-box algorithms (eg, back propagation artificial neural network [BPANN], random forest [RF], and support vector machine [SVM]), it generates easily interpretable decision rules, thereby extracting complex patterns hidden within the data.[30] This capability allows RST to provide deeper insights when analyzing real-world data.

Given the limitations of traditional methods, this study aims to use the RST method to explore the multifactorial issues and hidden rules surrounding HL. Specifically, this study seeks to develop an interpretable model using RST to analyze the health knowledge behavior patterns of male patients. This endeavor represents the first application of the RST method in this field. The objectives of this study include (1) calculating the importance of factors influencing HL levels to identify the key determinants affecting HL and (2) establishing a decision-rules model that links these factors with HL levels. The purpose of the objectives is to identify individual patients' behavior patterns and provide deeper insights for policymakers regarding intervention strategies.

Methods and Materials

The Chinese Version of HL Questionnaire

To date, various HL tools have been developed, ranging from traditional tools targeting individual skills and health education to tools with a multidimensional perspective.[31] The Chinese Resident Health Literacy Scale (CRHLS) was developed based on the Basic Knowledge and Skills for Resident Health Literacy published by the Ministry of Health of the People's Republic of China in 2008,[32] as detailed in a previous paper.[33] The scale has been widely used[16,34,35] and contains 80 items covering three main dimensions: basic knowledge and concepts (C_1), healthy lifestyle and behavior (C_2), and health skills (C_3). Combined with the main public health problems, health is divided into six HL types: *scientific concepts of health* (C_4), *infectious disease prevention and control literacy* (C_5), *chronic disease prevention and control literacy* (C_6), *safety and first aid literacy* (C_7), *basic medical literacy* (C_8), and *health information literacy* (C_9). The values of the nine factors were marked using two grades: pass (score = 1) and frail (score = 0). A total overall HL score higher than or equal to 53 is considered a pass; scores less than 53 indicate failure. *Passing* means having good HL, which is marked as "Yes" (Score = 1); *failing* indicates a lack of HL and is marked as "No" (Score = 0). Table 1 lists the index attributes and descriptions used in this study.

Table 1 The Attributes and Descriptions of the Study

Attributes	Descriptions	Values
Condition attributes		
Basic knowledge and concept (C_1)	Basic health knowledge and information acquired and understood by individuals.	Pass = 1; Fail = 0
Healthy lifestyle and behavior (C_2)	Habituated behavior beneficial to health.	Pass = 1; Fail = 0
Health skills (C_3)	Ability needed to manage health risk factors and protect and promote one's health.	Pass = 1; Fail = 0
Scientific concept of health (C_4)	Ability to seek a healthy state, promote physical and mental health, and adapt to society.	Pass = 1; Fail = 0
Infectious disease prevention and control literacy (C_5)	Understanding of knowledge related to prevention and control of infectious diseases.	Pass = 1; Fail = 0
Chronic disease prevention and control literacy (C_6)	Understanding of knowledge related to prevention and control of chronic diseases.	Pass = 1; Fail = 0
Safety and first aid literacy (C_7)	Ability to identify risk factors, prevent accidents, and deal with emergencies scientifically.	Pass = 1; Fail = 0
Basic medical literacy (C_8)	Understand, obtain, and utilize basic medical service information.	Pass = 1; Fail = 0
Health information literacy (C_9)	Ability to recognize one's health information needs and clear and reliable information access channels.	Pass = 1; Fail = 0
Decision attribute		
Health literacy	The ability to obtain, understand, and use basic health information and services to promote individual health.	1 Yes; 0 No

RST

Pawlak[36] first proposed the RST. It is a suitable method for dealing with multiple factors and attributes in data mining technology and can effectively deal with fuzzy and uncertain information.[27–29] Moreover, its introduction can extract hidden rules from a large amount of data that is difficult to handle manually. Hence, RST is convenient for analyzing the special practical significance represented by the data.[24,37] Currently, RST has been widely used in various fields, such as medical decisions in the medical field,[30,38,39] image processing,[40–42] risk assessment,[37,43,44] machine learning,[45–47] and knowledge acquisition[48,49] in the artificial intelligence field. We calculated the RST according to the research by Pawlak,[36,50] applying the computational steps described below.

Step 1: Information systems

According to the relevant information and observation data in the questionnaire, an information system S for analyzing male patients' HL was established. It comprises a set of objects U, attributes A, and attribute values V, and an information function F, as shown in Formula (1).

$$S = \{U, A, V, F\} \tag{1}$$

The set of objects U comprises all the objects participating in the questionnaire survey, as shown in Formula (2).

$$U = \{u_1, u_2, \ldots, u_n\} \tag{2}$$

The set of attributes A comprises the condition attribute set C and the decision attribute set D, as shown in Formula (3).

$$A = \{C \cup D\} \tag{3}$$

The influencing factors of HL, such as basic knowledge and concepts (C_1) and healthy lifestyle and behaviors (C_2), constitute the conditional attribute set C (see Formula [4]).

$$C = \{C_k\}, k = 1, 2, \cdots, 9 \tag{4}$$

HL (d_1) and non-HL (d_2) constitute the decision attribute set D; see Formula (5).

$$D = \{d_1, d_2\} \tag{5}$$

Set V represents the set of values corresponding to attribute $a \in A$; see Formula (6), where V_a is the value corresponding to attribute a.

$$V = \cup_{a \in A} V_a \tag{6}$$

The expression for the information function F is shown in Formula (7). This formula implies that for any $u_i \in U$ and $a \in A$, there is $F(u_i, a) \in V_a$.

$$F : U \times A \to V \tag{7}$$

Step 2: Indiscernibility relation and the upper and lower approximate sets

When some attributes of two objects contain the same information, they can be difficult to distinguish due to what is called an *indiscernible or equivalent relationship*. See Formula (8) for the definition. Among them, B is a non-empty subset of the set A, that is, $B \subseteq A$; I_B is the indiscernibility relation of B.

$$(u_1, u_2) \in I_B \Leftrightarrow F(u_1, a_b) = F(u_2, a_b), \forall a_b \in B \tag{8}$$

RST defines the upper approximation set $UA(X)$ and the lower approximation set $LA(X)$ (see Formulas [9] and [10]). where X is a partial set of U; I_B (.) is the equivalent class (basic set) of the indiscernible relation B; and $pos_B(X)$ is a positive field that determines all the elements of set U that belong to set X when considering a set B of attributes.

$$pos_B(X) = LA(X) = \{u_i \in U : I_B(u_i) \subseteq X\} \tag{9}$$

$$UA(X) = \{u_i \in U : I_B(u_i) \cap X \neq \emptyset\} \tag{10}$$

Steps 3: Attribute dependence and classification accuracy

RST defines the classification accuracy $\rho_B(E)$, which is used to determine the accuracy of the approximate set, as shown in Formula (11) where *card* (.) represents the number of set elements, X_i represents a classification set, and E can be expressed as $E = \{X_1, X_2, \cdots, X_n\}$.

$$\rho_B(E) = \frac{\sum card(LA(X_i))}{\sum card(UA(X_i))} \tag{11}$$

Moreover, the classification attribute dependency degree $\mu_B(E)$ is defined, which is used to express the ratio of the elements in the set U to E, as shown in Formula (12).

$$\mu_B(E) = \frac{\sum card(pos_B(X_i))}{card(U)} \tag{12}$$

Step 4: Important attribute set

Obtaining a set of important attributes is helpful in identifying the key factors that determine whether male patients have HL. An attribute's importance can be evaluated by the difference in the changes caused by deleting it. The greater the difference in the changes caused, the more important the attributes are, and vice versa. Therefore, the importance of a certain conditional attribute $a \in C$ can be calculated according to the Formula (13). The value range of importance $\eta_{(C,D)}(a)$ is [0,1]. The closer $\eta_{(C,D)}(a)$ is to 1, the more important the conditional attribute a is.

$$\eta_{(C,D)}(a) = 1 - \frac{\mu_D(C - \{a\})}{\mu_D(C)} \tag{13}$$

Step 5: Decision rules

Decision rules are a means of making decisions. The decision language is described by IF-THEN rules. For example, if $f(x, C_1)$, $f(x, C_2)$, $f(x, C_k)$, then x belongs to d_1 or d_2, where $x \in U$ (simplifies the decision language to $C \to D$). The decision rules' strength is shown in Formula (14).

$$\sigma_S(C, D) = \frac{\mathrm{supp}_S(C, D)}{card(U)} \tag{14}$$

Among them, $\mathrm{supp}_s(C,D)$ is the number of rules $C \to D$ supported under the information system S.

Ethics Statement

Information on all participants was collected anonymously. This study was approved by the Ethics Committee (IRB) of Taizhou Hospital of Zhejiang Province, affiliated with Wenzhou Medical University (ID: ENHM2020003). All procedures were performed according to institutional ethical guidelines and adhered to the principles of the Declaration of Helsinki. All participants were informed about the purpose, structure, and criteria of the study. Additionally, their informed consent was obtained.

Study Population

In this study, a convenience sampling method was used to collect questionnaires on-site from July 2020 to September 2020 for male patients of a hospital in China. Among the 212 patients surveyed, 206 (97%) completed the survey. The respondents' background information is presented in Table 2. The participants were male patients in a large general hospital in China. Patients aged 20 to 39 years accounted for the majority (62%), 73 with high school education or below (35%), and 133 with a college education or above (65%). About 20% were public institution staff, 13% were agricultural workers, 32% were students, and 15% were enterprise staff. A total of 92% had chronic diseases.

Research Design and Analysis Process

First, according to the questionnaire developed by the CRHLS, survey data of male patients from individual hospitals were collected. Second, the RST was used to identify key factors and decision rules for male patients' HL. Finally, the analysis of the results explains how they can help hospital administrators provide improvement directions. The research flow is illustrated in Figure 1.

Results

Degree of Importance of Each Condition Attribute

Using Formula (13), the key factors to identify whether male patients have HL can be obtained based on the survey data of 206 participants. The weights of all HL factors are shown in Table 3. The results showed that the order of importance of all factors, from high to low, was as follows: "health skills (C_3)", "basic knowledge and concept (C_1)", "healthy lifestyle and behavior (C_2)", "scientific concept of health (C_4)", "basic medical literacy (C_8)", "infectious disease prevention and control literacy (C_5)", "health information literacy (C_9)", "chronic disease prevention and control literacy (C_6)", and "safety and first aid literacy (C_7)". "Basic knowledge and concepts (C_1)" and "health skills (C_3)" are important factors in identifying whether male patients have HL, and their importance is much higher than that of the other seven factors.

Table 2 Respondent Background Information for the Case Study

	Sample Size	Frequency (%)
Age		
Under 20	42	20%
20–39	127	62%
40 and above	37	18%
Education		
High school and below	73	35%
College and above	133	65%
Occupation		
Public institution staffs	41	20%
Agricultural workers	27	13%
Students	66	32%
Enterprise staffs	31	15%
Other	41	20%
Whether you had chronic diseases?		
Yes	189	92%
No	17	8%

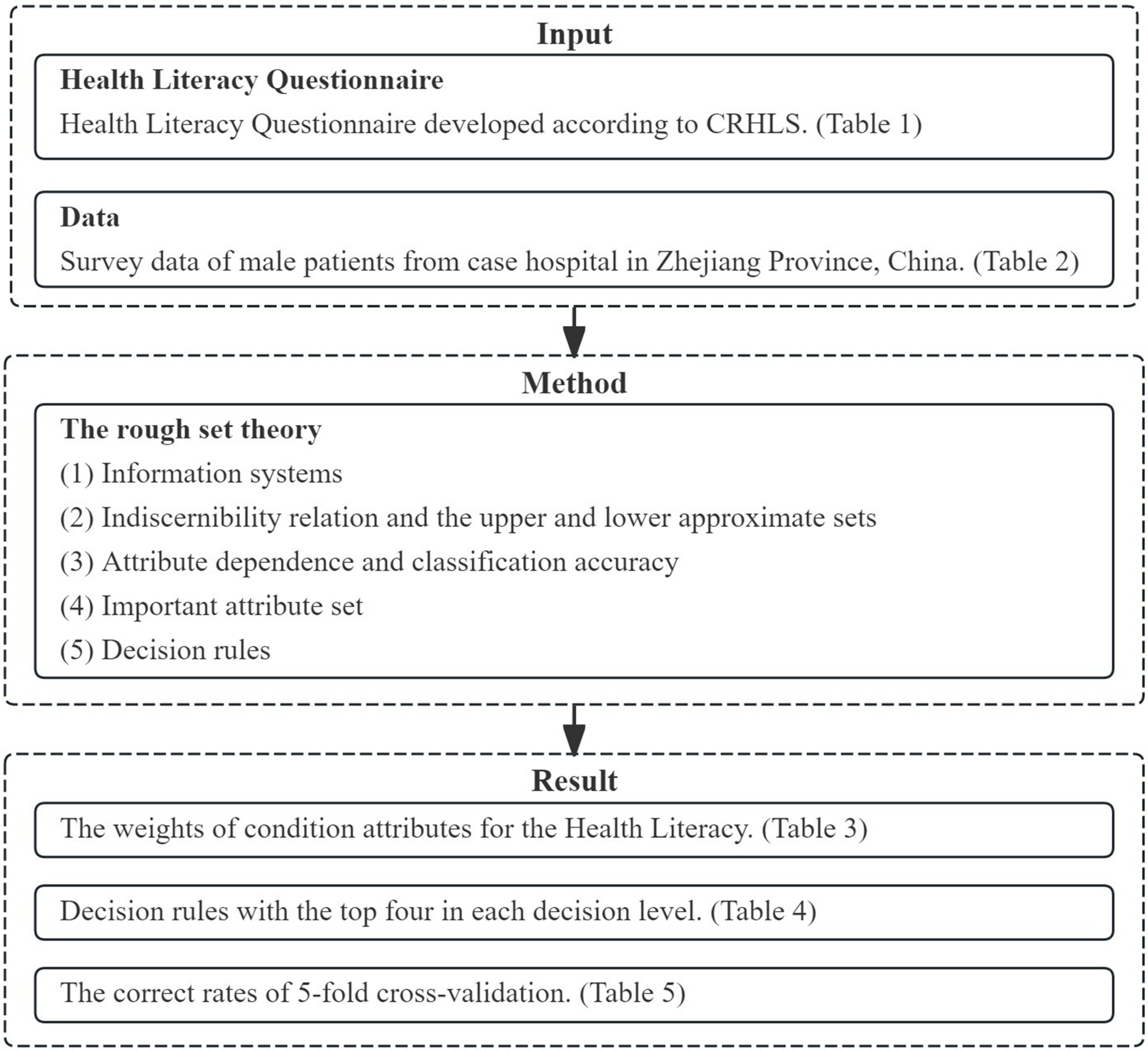

Figure 1 The research flow chart.

Decision Rules

RST can explain the existing rules of the original datasets using minimum coverage rules. It helps to understand the relationship between decision level (decision attribute) and factors (condition attribute) and explains this relationship with the least number of decision rules.

A total of 20 decision rules were summarized according to the RST. Among them, 10 were used to explain having HL, and 10 were used to explain not having HL. The first four primary decision rules were selected for each decision level to understand the primary rules for the different decision levels (Table 4). Considering Rule 1 as an example, 60.19% of male patients do not have HL, and there are three situations: basic knowledge and concepts (C_1) = 0/Fail, healthy lifestyle and behavior (C_2) = 0/Fail, and health skills (C_3) = 0/Fail.

To further determine the importance of conditional attributes relative to decisions from these decision rules, this study summarizes the frequency of these conditional attributes' occurrences. When the decision attribute is "No (do not have HL)", "healthy lifestyle and behavior (C_2) = 0/Fail" and "health skills (C_3) = 0/Fail" appear thrice; "basic knowledge and

Table 3 The Weights of Condition Attributes for the Health Literacy

Attributes	Degree of Importance	Weight
Basic knowledge and concept (C_1)	0.089	0.169
Healthy lifestyle and behavior (C_2)	0.071	0.135
Health skills (C_3)	0.119	0.225
Scientific concept of health (C_4)	0.065	0.124
Infectious disease prevention and control literacy (C_5)	0.048	0.090
Chronic disease prevention and control literacy (C_6)	0.030	0.056
Safety and first aid literacy (C_7)	0.006	0.011
Basic medical literacy (C_8)	0.065	0.124
Health information literacy (C_9)	0.036	0.067
Sum	0.530	1.000

Table 4 Decision Rules with the Top Four in Each Decision Level

No.	Conditions	Decision	Number of Objects
Rule 1	(C1= 0) and (C2 = 0) and (C3 = 0)	No	60.19% (62/103)
Rule 2	(C2 = 0) and (C3= 0) and (C6 = 0) and (C9= 0)	No	60.19% (62/103)
Rule 3	(C1 = 0) and (C2 = 0) and (C9 = 0)	No	60.19% (62/103)
Rule 4	(C3 = 0) and (C4 = 0) and (C8 = 0)	No	54.37% (56/103)
Rule 5	(C3= 1) and (C4) = 1) and (C5 = 1)	Yes	50.49% (52/103)
Rule 6	(C2= 1) and (C3= 1) and (C4 = 1) and (C5) = 1) and (C9 = 0)	Yes	33.00% (34/103)
Rule 7	(C3 = 1) and (C4 = 1) and (C8 = 1) and (C9 = 0)	Yes	21.36% (22/103)
Rule 8	(C1 = 1) and (C2 = 1) and (C9 = 1)	Yes	17.48% (18/103)

concept (C_1) = 0/ Fail" and "health information literacy (C_9) = 0/Fail" appear twice; and "chronic disease prevention and control literacy (C_6) = 0/ Fail" and "basic medical literacy (C_8) = 0/Fail" appear once. When the decision attribute is "Yes (have HL)", "health skills (C_3) = 1/Pass" and "scientific health concepts (C_4) = 1/Pass" appear thrice; "healthy lifestyle and behavior (C_2) = 1/Pass" and "infectious disease prevention and control literacy (C_5) = 1/Pass" appear twice; and "basic medical literacy (C_8) = 1/Pass" and "health information literacy (C_9) = 1/Pass" appear once.

Validation of the RST Model

The decision rules based on the RST revealed the relationship between HL and the conditional attributes of male patients. To verify the decision rule's reliability, this study adopts five-fold cross-validation to verify its accuracy. Among them, 80% of the data were selected as training samples, and 20% were selected as test samples for verification. Moreover, this study also compares three common data mining methods: RF, BPANN, and SVM. All the methods were verified by 5-fold cross-validation. Table 5 shows the correct and average correct rates for the five processes. The average correct rates for RST, RF, BPANN, and SVM were 89.52%, 91.36%, 93.33%, and 92.20%, respectively.

Table 5 The Correct Rates of 5-Fold Cross-Validation

No.	RST	RF	BPANN	SVM
1	85.71%	91.26%	90.48%	87.80%
2	90.47%	91.26%	92.86%	92.68%
3	85.71%	91.26%	97.62%	95.12%
4	95.23%	91.75%	95.24%	92.68%
5	90.47%	91.26%	90.48%	92.68%
Average correct rates (%)	89.52%	91.36%	93.33%	92.20%

Discussion

Key Factors Influencing Health Literacy

The importance of conditional attributes (as shown in Table 3) indicates that "basic knowledge and concepts (C_1)" and "health skills (C_3)" are the key factors in identifying whether male patients have HL. Health knowledge is the premise and foundation of healthy behavior, which can help inspire and persist behavior and is important to overall health.[51,52] Without basic health knowledge, understanding the importance of a healthy lifestyle and maintaining healthy habits can be difficult.[53] Therefore, "basic knowledge and concept (C_1)" is an important factor in identifying whether the patient has sufficient HL. Health skills are all kinds of skills that can be mastered to acquire, process, understand, and communicate health information.[54] There is also a direct relationship between personal health skills and health levels.[55] Health knowledge can affect health skills to a great extent, and the latter directly or indirectly affects health behaviors.[54] Therefore, "health skills (C_3)" are important to the HL of male patient populations.

Clinical Practice

From the perspective of decision rules (as shown in Table 4), decision-makers can further understand the cognitive rules of male patients' HL under different combinations of conditional attributes. When the combination conforms to the contents of Rules 5 to 8, the patient is considered to have good HL. Patients' health skills; scientific concepts of health, healthy lifestyles, and behaviors; and infectious disease prevention and control literacy, basic medical literacy, and health information literacy can be used to identify their cognitive behaviors related to HL to varying degrees. Patients with low HL must change their condition-attribute state combinations. For example, in Rule 1, patients lacking basic knowledge and ideas, healthy lifestyles and behaviors, and health skills are considered to not have HL. Therefore, decision-makers can guide patients to acquire healthy lifestyles and master health skills by providing them with health education so that they can have cognitive behaviors related to HL.

It can be seen from Rules 1 to 4 that the lack of healthy lifestyle and behavior health skills, basic knowledge and concepts, health information literacy, and chronic disease prevention and control literacy can be identified as cognitive behaviors without HL to varying degrees. Therefore, hospital decision-makers can improve the cognitive behavior of male patients' HL by changing the combination of these conditions and attributes.

Comparative Analysis of Different Decision Models

From the accuracy results of the five-fold cross-validation of the RST, RF, BPANN, and SVM (Table 5), the results of these models are highly reliable. Existing research has used three common data mining methods (BPANN, RF, and SVM) to assess HL and identify key factors influencing HL levels.[56–58] However, these methods are considered black-box algorithms[59] that are incapable of capturing individual patient behavior patterns or providing decision-makers with deeper intervention insights.[60] In contrast, RST can employ regular expressions to elucidate behavioral patterns between key HL factors and HL levels.[36] This way of exploring importance and decision rules can help hospital decision-makers or managers understand the clinical behavior of most patients and provide appropriate evidence-based medical or nursing interventions.

Limitations

There are some limitations in this study. First, our survey participants included only male patients in hospitals, and personal information factors, such as gender and age, were not considered in data analysis. Hence, the results of this study may only be applicable to the respondents who participated in the survey and may not be extrapolated to other hospitals or survey respondents.

Conclusions

This study was the first to use RST to identify the key factors and decision rules affecting male patients' HL levels via the questionnaire devised by the Ministry of Health of the People's Republic of China and survey data from hospitals. The results related to key factors can help individuals, decision-makers, and healthcare providers understand critical indicators for improving HL levels. Decision rules outcomes aid in understanding each patient's HL level and in developing tailored improvement strategies for male patients to enhance their HL. The model in this study demonstrates high reliability. Moreover, in contrast to other black-box algorithms (BPANN, RF, and SVM), RST can be used to identify individual patient behavior patterns using decision rules that are appropriately interpretable This identification can help decision-makers understand clinical behaviors among most patients, thereby facilitating evidence-based medical or nursing interventions accordingly. Therefore, the main contributions of this study include the following: (i) HL plays an important role in China's development; However, few studies have used quantitative methods from the patients' perspective to explore how to identify and improve patients' HL levels; thus, this study compensates for the research gaps. (ii) In contrast to previous studies, this study used the RST to obtain the cognitive situation of male patients' HL, demonstrating that it is highly reliable and feasible. (iii) The model and results can be applied in clinical nursing practice. The key factors and decision rules obtained can help hospital administrators guide male patients in improving their HL ability more easily. Moreover, future research can use the fuzzy rough set method or other data-mining methods to determine the factors of HL. We can also further study the HL of more patients with various characteristics, including different genders and sexes.

Data Sharing Statement

The original contributions presented in the study are included in the article, and further inquiries can be directed to the corresponding author/s.

Ethics Approval and Consent to Participate

Information on all participants was collected anonymously. This study was approved by the Ethics Committee (IRB) of Taizhou Hospital of Zhejiang Province, affiliated with Wenzhou Medical University (ID: ENHM2020003). All procedures were performed according to institutional ethical guidelines and adhered to the principles of the Declaration of Helsinki. All participants were informed about the purpose, structure, and criteria of the study. Additionally, their informed consent was obtained.

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Disclosure

The authors declare that they have no conflicts of interest.

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