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Analysis of Factors Influencing Exercise Benefits and Barriers in Cardiovascular Disease Patients Visiting the Emergency Department Based on Machine Learning

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ABSTRACT

Objective: To investigate the exercise benefits/barriers and influencing factors among cardiovascular disease (CVD) patients seeking emergency care. Methods: A convenience sampling method was used to select CVD patients who visited the emergency department of a tertiary hospital in Chengdu from December 2023 to July 2024 as the study subjects. The investigation was conducted through medical record review and on-site questionnaire surveys. The research tools included a general information questionnaire, the International Physical Activity Questionnaire-Short Form (IPAQ-SF), the Exercise Benefits/Barriers Scale (EBBS), the Exercise Self-Efficacy Scale, the Patient Health Questionnaire-9 (PHQ-9), and the Social Support Rating Scale (SSRS). Data were entered into Excel and statistically analyzed using SPSS 26.0. Results: Among the 1080 patients, 62.9% did not meet physical activity standards. Depression and social support explained 48.0% of the total variance in exercise benefits/barriers. The random forest algorithm performed best in predicting influencing factors. Conclusion: CVD patients seeking emergency care are generally insufficiently active, with depression and social support significantly impacting exercise benefits/barriers.

KEYWORDS

Emergency care; Cardiovascular disease; Physical activity; Exercise benefits/barriers; Machine learning

1. INTRODUCTION

Cardiovascular disease (CVD) is one of the most common chronic diseases and the leading cause of death globally, with a high rate of emergency department visits. Studies by Rui PKK et al. found that over seven consecutive years, hypertension-related cases accounted for 23.6% of all emergency department visits in the United States. Shen Jiaxin conducted an analysis of 240,000 emergency department patients, and Wei Pengli analyzed 54,900 emergency department patients, both concluding that CVD is among the top three diagnoses. Currently, the assessment of CVD treatment outcomes and burden is primarily based on hospital inpatient data, often overlooking the emergency department. In fact, the emergency department is often the first point of care for patients with severe and potentially life-threatening conditions. For many CVD cases, the onset can be sudden and fatal, sometimes leading to death before hospitalization. A significant portion of CVD-related deaths occurs in the emergency department, such as acute myocardial infarction (16.4%), heart failure (5.8%), intracranial hemorrhage (8.1%), and stroke (2.7%).

Exercise, as a frontline intervention for CVD, has been proven effective. The "Exercise is Medicine" (EIM) model promotes prescribing exercise similarly to medication. However, CVD patients visiting the emergency department often require urgent and immediate treatment, although some patients proactively seek care before their condition worsens due to a strong sense of self-care.

Exercise benefits and barriers are key factors influencing physical and psychological states related to exercise. The perceived benefits and barriers to exercise are predictive of physical activity levels and are crucial for improving exercise participation. Perceived exercise benefits refer to an individual's recognition of the positive effects of exercise, while perceived barriers refer to the factors hindering participation in exercise. Current research mainly focuses on cardiovascular health, weight management, and reducing chronic disease risk. Regarding exercise benefits, the focus is on physical health benefits such as muscle strength, bone density, and overall fitness, and psychological health aspects like anxiety and depression. Exercise barriers include lack of motivation, doubts about exercise efficacy, fear of injury, and time constraints as significant psychological obstacles. Social and cultural factors such as family responsibilities and gender roles exacerbate these barriers. Environmental and economic factors, including the lack of safe exercise venues, limit outdoor exercise opportunities, and economic conditions also play a significant role as many people cannot afford fitness facilities due to financial pressures.

Previous studies have not analyzed exercise benefits and barriers among CVD patients in the emergency department setting. Research in the emergency department can capture CVD patients who may not be included through conventional admission routes. Different machine learning methods can be used to identify the most suitable model for determining the influencing factors of exercise benefits and barriers.

2. MATERIALS AND METHODS

2.1. Study Design

A total of 1018 CVD patients who visited the emergency department of a large tertiary hospital in Chengdu from December 2023 to July 2024 were selected. Inclusion criteria: (1) Diagnosed with CVD during the visit or previously recorded in medical records; (2) Age ≥ 18 years; (3) Able to communicate normally, complete the questionnaire, and provide complete data. Exclusion criteria: (1) Patients with mental illness or intellectual disabilities; (2) Patients with musculoskeletal diseases or other severe conditions significantly affecting physical activity; (3) Participants in other interventional studies; (4) Long-term bedridden or wheelchair users. All patients provided informed consent, allowing their data to be used for further clinical research. The study protocol was approved by the Sichuan Provincial People's Hospital Ethics Committee (Approval No. 2024-414) and registered with the Chinese Clinical Trial Registry (ChiCTR2400088116).

2.1.1. Data Collection Process

The data were collected in the emergency waiting area of a tertiary hospital in Chengdu after triage. Once the questionnaires were completed, they were immediately collected by the researchers and coded.

2.1.2. Research Tools General Information

(1) Demographic Data: This includes the patient's age, gender, education level, living situation, occupation, health insurance, monthly income, marital status, etc. (2) Disease-Related Information: This includes smoking habits, alcohol consumption, dietary habits, height, weight, waist circumference, etc. (3) Emergency Visit Information: This includes vital signs, diagnosis, disease classification, etc.Exercise Benefits/Barriers Scale (EBBS):The EBBS was developed by Sechrist and colleagues in the United States and consists of 43 items, including 29 items on exercise benefits and 14 items on exercise barriers. It is used to understand the perceived benefits of participating in

exercise and the factors that hinder participation. The scoring for the exercise benefits items ranges from 4 (strongly agree) to 1 (strongly disagree), while the exercise barriers items are reverse scored. The sum of the two categories' scores represents the EBBS score. In 2009, Chinese scholar Zheng Jing translated and validated the scale, which was initially applied to patients undergoing maintenance hemodialysis. In that study, the Cronbach's alpha coefficient for the EBBS was 0.94. In this study, the Cronbach's alpha coefficient for the EBBS was 0.916.International Physical Activity Questionnaire-Short Form (IPAQ-SF):The IPAQ-SF, developed in 1997 by the International Physical Activity Work Group, is a widely recognized tool for measuring physical activity levels subjectively.Self-Efficacy for Exercise Scale (SEE):This scale was developed by Resnick and colleagues, with lower scores indicating poorer exercise self-efficacy. In this study, the Cronbach's alpha coefficient for the SEE was 0.937.Social Support Rating Scale (SSRS):The SSRS was developed by Xiao Shuiyuan and his team in 1993. In this study, the Cronbach's alpha coefficient for the SSRS was 0.707.Patient Health Questionnaire-9 (PHQ-9):The PHQ-9 assesses depression by asking respondents to rate their experiences over the past two weeks. It is a reliable and valid tool for screening and assessing depression. In this study, the Cronbach's alpha coefficient for the PHQ-9 was 0.772.

2.2. Statistical Analysis

All data were entered into Excel to create a database, and statistical analysis was performed using SPSS 26.0. The significance level was set at $\alpha=0.05$, with $P<0.05$ indicating statistical significance.

3. RESULTS

3.1. Basic Characteristics

A total of 1018 CVD patients were included, with 502 males (49.31%) and 516 females (50.69%). The age range was 18-82 years (mean age: 44.28±15.73). Marital status: 250 unmarried (24.56%), 690 married (67.78%), 78 divorced or widowed (7.66%). Education level: 412 with junior high school or lower (40.47%), 182 with high school or technical school (17.88%), 382 with college or university (37.52%), and 42 with a master's degree or higher (4.13%). Living situation: 160 living alone (15.72%), 858 not living alone (84.28%). Employment status: 631 employed (62%), 387 unemployed (38%). Monthly income: 403 earning less than 3,000 yuan (39.59%), 333 earning 3,000-5,000 yuan (32.71%), 205 earning 5,001-10,000 yuan (20.14%), 77 earning more than 10,000 yuan (7.56%).

3.2. Emergency Visit and Health Status

Table 1. Emergency Visit and Health Status

variable	n	%
BMI		
underweight	29	2.8
normal	434	42.6
superheavy	385	37.8
obesity	170	16.7
body temperature		
normal	1018	100
pulse		
normal	923	90.7
too fast	95	9.3
breathe		
normal	916	90
too fast	102	10
blood pressure		
normal	470	46.2
high blood pressure	527	51.8
drink		
no drinking	647	63.6
occasional drink	160	15.7
drink on a regular basis	211	20.7
smoke		
never smoked	551	54.1
used to smoke	373	36.6
current smoking	94	9.2
high salt diet		
yes	316	31
no	702	69
high fat diet		
yes	348	34.2
no	670	65.8
take medicine		
never take medication	740	72.7
unclear	63	6.2
take medicine consistently	155	15.2
isntermittent medication	60	5.9
primary diagnosis of disease		
coronary heart disease	188	18.5
high blood pressure	203	19.9
diabetes	207	20.3
stroke	225	22.1
hyperlipidemia	195	19.2
Number of other diseases combined		
0	691	67.9
1	213	20.9
2	98	9.6
3	16	1.6
time period of treatment		
8AM-5:59PM	332	32.6
6PM-11:59PM	346	34.0
0AM-8:00AM	340	33.4

3.3. Influence of Exercise Benefits and Barriers

The average score for exercise benefits/barriers was 70.82±13.56, with 37.1% meeting the physical activity standards and 62.9% not meeting the standards. Significant differences were found in the comparison of exercise benefits/barriers across different demographic and health conditions. Regression analysis was performed with the average score of exercise benefits/barriers as the dependent variable, and the results are summarized as follows:

Table 2. Model Summary

R	R^2	Adjusted R^2	Standard Error
0.638	0.407	.403	10.47949

Table 3. ANOVA Results

	quadratic sum	degree of freedom	mean square	F	significance
Regression	75783.686	4	18945.921	172.602	0.000
residual error	110973.842	1011	109.766		
Summary	186757.528	1015			

Table 4. Regression analysis table

	unnormalized coefficient		standardization coefficient	t	
	B	standard error	Beta		significance
constant	65.112	2.370		27.475	.000
depression	.716	.036	.607	19.663	.000
sports self-efficacy	-.029	.026	-.030	-1.112	.267
Total energy consumed by physical activity	.000	.000	.044	1.561	.119
social support	-.172	.053	-.081	-3.277	.001

3.4. Establishment and Performance Evaluation of Different Machine Learning Regression Models

In this experiment, various factors influencing the development of the disease were selected as features to form a data surface, and the interior-point method was used to solve the data. To better evaluate the data analysis results of each machine learning model, mean squared error (MSE), mean absolute error (MAE), and the coefficient of determination (R^2) were used as evaluation metrics. Machine learning algorithms such as Random Forest (RF), Support Vector Machine (SVM), and Recurrent Neural Network (RNN) were employed to perform regression analysis on factors affecting the mobility of cardiovascular disease patients in the emergency department, yielding the following results.

Table 5. Regression Model Analysis Assessments

	MSE	MAE	R^2
RF	0.022	0.129	0.917
SVM	0.033	0.156	0.854
RNN	0.037	0.164	0.827

4. DISCUSSION

In this study, it was found that 62.9% of cardiovascular disease (CVD) patients who visited the emergency department did not meet the recommended level of physical activity. The majority of these patients were middle-aged, married, with a secondary school education or lower, and living with others. Among them, 37.8% were overweight, 51.8% had hypertension, and 34.2% had a high-fat diet. During middle age, the body's metabolism gradually slows down, and life stress increases. Additionally, this group may have lower levels of health knowledge and unhealthy lifestyle habits, which may collectively contribute to an increased risk of developing cardiovascular diseases [15]. The proportion of overweight individuals was 37.8%, hypertensive patients accounted for 51.8%, and 34.2% had a high-fat diet. These factors have been widely recognized as significant risk factors for cardiovascular diseases [16].

The emergency visits of CVD patients were concentrated between 6 PM and midnight. The evening is a time when many people unwind from the day's stress, but it may also be a peak period for various cardiovascular events. Studies have shown that the excitability of the sympathetic nervous system gradually accumulates during the day, leading to phenomena such as blood pressure fluctuations and increased heart rate at night, which raises the likelihood of cardiovascular events [17]. Additionally, the evening might be a time when people have irregular eating habits or engage in binge eating, behaviors that could trigger acute cardiovascular events [18].

Among the factors influencing the barriers to exercise benefits, depression and social support were found to account for 40.3% of the variance in the regression model. This indicates that these two factors are the main influences on exercise benefit barriers. Depression, as a common psychological disorder, has been widely documented to significantly reduce an individual's activity levels and motivation to exercise. Patients with depression often exhibit symptoms of fatigue, loss of interest, and lack of motivation, which can lead to a negative attitude toward exercise, subsequently affecting the frequency and effectiveness of their actual participation in physical activities [19]. Furthermore, depressive symptoms may increase the perception of exercise barriers because depressed individuals often find it difficult to experience the positive emotional and physical health benefits of exercise [20].

Social support is considered a key factor in promoting healthy behaviors. Support from family, friends, and the community can not only provide emotional comfort but also enhance the individual's ability to adhere to behaviors. Social support is closely related to higher levels of exercise participation, especially when coping with life stress or psychological issues. Social support can provide motivation and practical help, alleviating the difficulties associated with exercising [21]. A reduction in social support levels might be one of the reasons for worsening depressive symptoms; conversely, the presence of depressive symptoms may also lead to a reduced perception of social support [22]. This interaction may further affect the maintenance of exercise behavior. Individuals lacking social support are more likely to fall into a depressive state, leading to greater psychological barriers to exercise, while those in a depressive state may perceive reduced social support, further diminishing their willingness and ability to engage in exercise.

The results of the machine learning analysis showed that the Random Forest algorithm performed the best among cardiovascular disease patients visiting the emergency department. This study's findings are consistent with existing research, further validating the advantage of the Random Forest algorithm in handling complex medical data [23]. The risk factors for cardiovascular diseases are numerous and intertwined, including age, blood pressure, body mass index, dietary habits, family history, and others. The Random Forest algorithm can process these multidimensional data through multiple decision tree models and effectively capture the complex interactions between variables [24]. Moreover, the Random Forest algorithm has strong noise resistance, maintaining high accuracy even when dealing with missing data or outliers. This is particularly important in emergency scenarios, where data are often highly imbalanced and incomplete. Compared to other machine learning algorithms, the

Random Forest algorithm has demonstrated greater stability and accuracy in handling large-scale medical data.

5. CONCLUSION

This study summarized the characteristics of emergency department visits by cardiovascular disease patients and the influencing factors of exercise benefit barriers, while also validating the superiority of the Random Forest algorithm in processing data related to emergency cardiovascular disease patients. These findings provide important evidence for clinical interventions and data analysis, emphasizing the need for comprehensive preventive strategies for high-risk populations and the application of efficient algorithms.

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