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Activity Recommendation Model Using Rank Correlation for Chronic Stress Management

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Abstract: Korean people are exposed to stress due to the constant competitive structure caused by rapid industrialization. As a result, there is a need for ways that can effectively manage stress and help improve quality of life. Therefore, this study proposes an activity recommendation model using rank correlation for chronic stress management. Using Spearman's rank correlation coefficient, the proposed model finds the correlations between users' Positive Activity for Stress Management (PASM), Negative Activity for Stress Management (NASM), and Perceived Stress Scale (PSS). Spearman's rank correlation coefficient improves the accuracy of recommendations by putting a basic rank value in a missing value to solve the sparsity problem and cold-start problem. For the performance evaluation of the proposed model, F-measure is applied using the average precision and recall after five times of recommendations for 20 users. As a result, the proposed method has better performance than other models, since it recommends activities with the use of the correlation between PASM and NASM. The proposed activity recommendation model for stress management makes it possible to manage user's stress effectively by lowering the user's PSS using correlation.

Keywords: medical data mining; chronic stress; correlation; activity recommendation model; stress management; mental healthcare

1. Introduction

Currently, Korea is experiencing political turmoil, anxiety, and stress over the future of the individuals, including the recession and unemployment crisis and the rise of the unemployed. Also, constant competition with others is being created. Teenagers, for example, spend most of their time at school and are under stress due to fierce competition for entrance examinations, and the suicide rate is also increasing. According to the Statistical Korea [1], the GDP ranks 11th, while the happiness index ranks 58th, the suicide rate is 1st, and the satisfaction level of students is the lowest among OECD countries. With these social problems emerging, research, and efforts to solve them have become increasingly important. Stress, the most representative and most influential of mental health, refers to the physical, mental, behavioral response, or adaptation of an individual to external stimuli or changes. Stress is classified as good stress (Eustress) and bad stress (Distress) [2]. Eustress can improve one's quality of life after the proper response to and recovery from the stress. Distress can last despite one's adaptation or treatment and can cause such symptoms as depression and anxiety. Chronic and continuous stress can lower one's quality of life, whereas the appropriate and effective use of good stress can develop one's life [2,3]. In the study by Hans Selye, stress is divided into three stages: stage 1 'Alarm', stage 2 'Resistance', and stage 3 'Exhaustion'. Selye also suggested the model in which if one's stress lasts and goes into stage 3 'exhaustion', it is possible to develop into a physical/psychological disease [3].

Continuous exposure to excessive stress can cause acute stress or chronic stress as an aftereffect. Chronic stress incurs since the causes of stress are not resolved. Therefore, a person who has chronic stress experiences lowered digestive function and a rise in heart rate and consequently has such symptoms as chronic indigestion, insomnia, anxiety, and depression. In chronic stress, adrenocortical hormones like cortisol continue to be secreted. A healthy person can quickly generate antibodies for viruses, bacteria, and cancer cells. However, it is difficult for people with chronic stress to produce antibodies. Thus, in people with chronic stress, hormones like cortisol significantly lower the body's immunity, and consequently, the immune function of antibodies is weakened [4]. Therefore, excess stress predisposes people to other diseases. It is necessary to manage and resolve stress usually.

Samsung Medical Center [5] classified stress management methods into three categories: management in daily life, relaxation management, and professional help. Stress management in daily life is divided into personal and social aspects. Personal aspect refers to regular lifestyles such as eating, exercising, and having enough sleep time in an individual's daily life. Individuals need to respond and manage to stressors positively and actively. In the social aspect, most of the stressors are interpersonal. The way to manage this is smooth communication. It is also a good idea to mediate stress through desirable interpersonal relationships, and positive interventions are essential. Because, depending on your perspective and attitude, the same stress can be felt by one person as Eustress and by another as Distress. A relaxation technique is a method of deliberately cutting off tension and stress and periodically resting and relaxing in a situation that causes an abnormality of the overall stress control system. Relaxation sometimes helps to relieve stress, rest the sympathetic nerves sufficiently, and balance the autonomic nerves. Typical relaxation techniques include meditation, yoga, prayer, progressive muscle relaxation, deep breathing, exercise, and hobby activities that can be immersive in joy. Finally, it is professional help. These methods can be negative factors in situations where stress management is not possible due to management in daily life and relaxation management or exhaustion caused by severe stress. Therefore, professional help is a fundamental solution to psychotherapy and medication through stress management specialists or psychiatrists.

The activity recommendation model proposed in this study finds the correlation of perceived stress scale with the use of Spearman's rank correlation coefficient. In this way, it recommends a user the activity for stress management to reduce distress and induce appropriate exposure of eustress. Therefore, by using the proposed model, a user can manage stress efficiently and enjoy a more productive life through exposure to eustress.

2. Materials and Methods

2.1. Stress Management Service Using the Perceived Stress Scale

The Perceived Stress Scale (PSS) developed by Sheldon Cohen is a psychological tool to measure one's stress perception [6]. PSS is the big scale used in the world to evaluate one's subjective stress degree in everyday life. A user answers within five minutes ten questions about the stress often felt for one month. The weighting value of the points for each question ranges from 0 to 4, in which '0' means feel no stress, '1' feel almost no stress', '2' sometimes feel stress, '3' feel stress often, and '4' feel stress very often.

The Validation of the PSS developed by Sheldon Cohen was carried out through three sample groups of students. Test results showed a high correlation between the PSS and the stress scale. The higher the total score of PSS, the more stress [7]. The PSS index of different stress levels identifies the cut-off criteria for PSS scores and stress levels. If the total score is 13 points and less, it means the normal stress status. In other words, a person's perceives its current stress as Eustress and has no serious stress factors, and therefore the stress can bring about a positive effect. Scores ranging from 14 to 16 mean mild stress which starts to be influential. If this stress lasts, it is possible to have distress. Scores ranging from 17 to 18 mean moderate stress which requires careful attention. Scores of 19 and higher mean incredibly severe stress. In this case, this stress is highly likely to develop into a mental disease so that it is required to seek professional help [8]. Figure 1 illustrates the PSS based stress management service process.

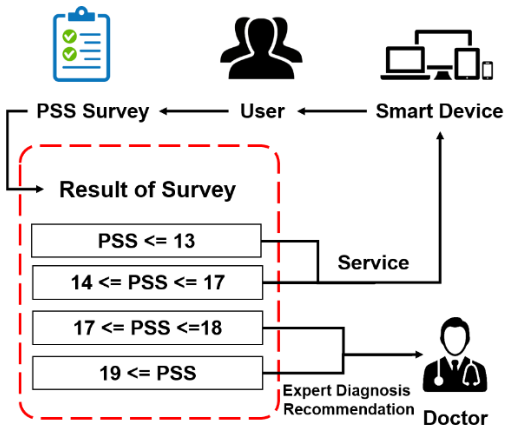

Figure 1. Process of stress management service using the Perceived Stress Scale (PSS).

Figure 1 shows appropriate services depending on the range of results based on the user's PSS results obtained from the survey. For example, normal stress below 13 points and mild stress between 14 and 16 points are continuously tracked through the smart device. It periodically performs the PSS test to observe the user's stress changes and provide appropriate chronic stress management. However, if the user is in a moderate stress state of 17 to 18 points or a very stressful state of more than 19 points, continuous stress management is not enough, and the state is considered to be very dangerous. Therefore, it is highly recommended to get help with stress management from experts through their diagnosis.

2.2. Detection Relation Using Correlation Coefficients

The correlation analysis [9] is a method of analyzing linear relationships between two variables in statistics and probability theory. Two variables may be independent or correlated with each other. At this time, the relationship between the two variables is called a correlation. The correlation coefficient is a measure of identifying the degree of correlation, which allows you to understand the correlation between the two variables but not to identify the causal relationship. The types of correlation coefficients include Pearson's correlation coefficient [10], Spearman's rank correlation coefficient [11], and Cramer's correlation coefficient [12]. Among them, the most commonly-used correlation coefficients are Pearson and Spearman. Pearson's correlation coefficient [10] is commonly used to find out the relationship between two variables. In statistics, the Pearson's correlation coefficient is a numerical value of quantifying the linear correlation between X and Y and has a value between −1 and +1. The values of +1, 0, and −1 mean perfect linear correlation, no relation, and negative linear correlation, respectively. The calculation method is to divide the covariance of two variables by the product of standard deviations. Figure 2 presents the correlation of variables to predict the weather. Figure 2 shows the correlation coefficients between RPCP, TMAX, TMIN, and RAIN. The variables used are as follows: PRCP means the amount of precipitation. TMAX means the maximum temperature for a day. TMIN means the minimum temperature for a day. RAIN means true and false for raining. This is TRUE if rain was observed on that day, or FALSE if it was not. The correlation coefficients are expressed in color according to the label on the right. It is blue as it gets closer to 1, red as it is −1, and white as it is 0. For example, RAIN and TMAX show a moderate red color because they show a correlation of −0.4. The same variable also appears blue because the correlation coefficient is unconditionally +1. Compared to the Pearson coefficient, the Spearman coefficient is rank-based and independent of non-parameters and size. The Spearman rank correlation coefficient is a nonparametric measure of statistically measuring statistical dependence between the ranks of two variables. It evaluates whether to explain the relationship between two variables well using a monotonic function. The Spearman rank correlation coefficient between two variables is equal to the Pearson correlation coefficient between the rank values of the two variables. However, Pearson's correlation coefficient evaluates linear relationships between two variables, while Spearman evaluates their monotonic relationships [13].

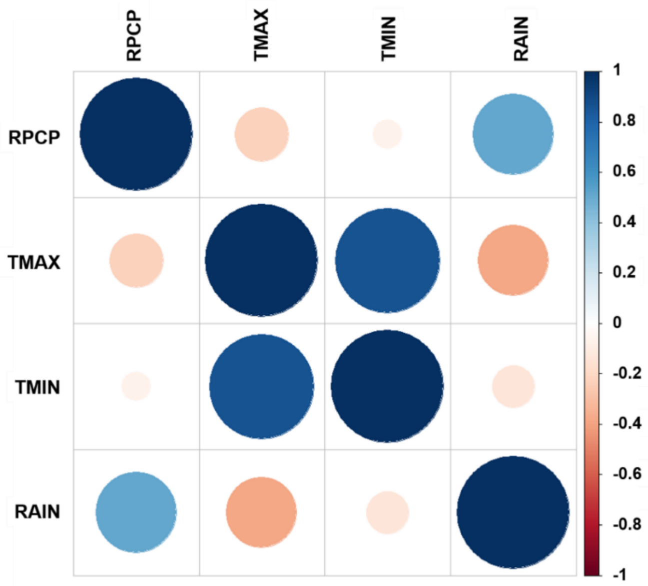

Figure 2. Correlation coefficients for weather prediction. PRCP-the amount of precipitation; TMAX-the maximum temperature for a day; TMIN-the minimum temperature for a day; RAIN-true and false for raining.

Without duplicate values, a perfect Spearman rank correlation of +1 and –1 occurs when each variable is a perfect monotonic function of another variable. Pearson's correlation coefficient is calculated only when both variables are present. As a result, it is challenging to process missing values. The Spearman's correlation coefficient, however, can perform better than Pearson because it calculates the basic rank even if there are missing values. Using the rank, it can also be used for ordinal rather than continuous variables. Taking advantage of these advantages, this paper uses the Spearman rank correlation coefficient. Formula (1) represents the formula of the Spearman rank correlation coefficient. d_i to the difference in the ith rank when sorting the values of two variables in order of size. n means the number of data.

$$\mathrm{p} = \frac{6\sum {d_i}^2}{n(n^2-1)}, \tag{1}$$

Mu Y et.al [14] proposed a decision tree and parallel implementation method based on Pearson's correlation. The proposed method uses the Pearson's correlation coefficient as a new quality measurement method to find the optimal splitting attribute and splitting point in the expansion of the decision tree. It also reflects the relationship between each attribute value and class distribution. At this time, each attribute has a vector for all attribute values. Pearson's correlation coefficient between the vector and the class distribution can measure the consistency. This gives a threshold value for determining whether the tree is extended, which solves the over-fitting problem.

Zhang WY et al. [15] measured the mixing patterns of the complex networks by the Spearman rank correlation coefficient. This compares the Pearson's correlation coefficient and Spearman's correlation coefficient in complex networks. If the network size is adequate, the results of the Spearman's correlation coefficient and Pearson's correlation coefficient are similar. As the network size increased, however, the Pearson correlation coefficient quickly converged to 0, resulting in no mixing pattern, and the Spearman's correlation coefficient showed good performance regardless of the network size.

2.3. Recommendation Technic in Healthcare

The recommendation system [16] obtains user information, calculates a similarity, and makes a cluster based on individuals' interest areas, logs, preferences, and bookmarks. It recommends the items of music, films, books, and others which users in a similar group seem to be interested in. The methods for recommendation are collaborative filtering, content-based filtering, and hybrid filtering. Collaborative filtering is the method of using the preferences of items and clustering users with similar patterns. It has the first-rater problem of excluding items from a recommendation list if there is no history of them [16,17]. Content-based filtering is the method of analyzing the content of items and using the similarities and attributes of obtained items. In other words, based on a user profile, it discovers and uses similarities of attributes for recommendation [18]. The method recommends items with a high similarity only so that it has the problem of over-specialization. Hybrid filtering is the method of resolving the cold-start problem and the over-specialization problem and improving performance in a combination of each filtering method [19]. By considering item attributes and rating data, it assigns a weighting value differently to recommend a proper item. The recommendation system developed recently uses hybrid filtering to increase the precision and recall of the prediction. Figure 3 shows the process of hybrid collaboration filtering.

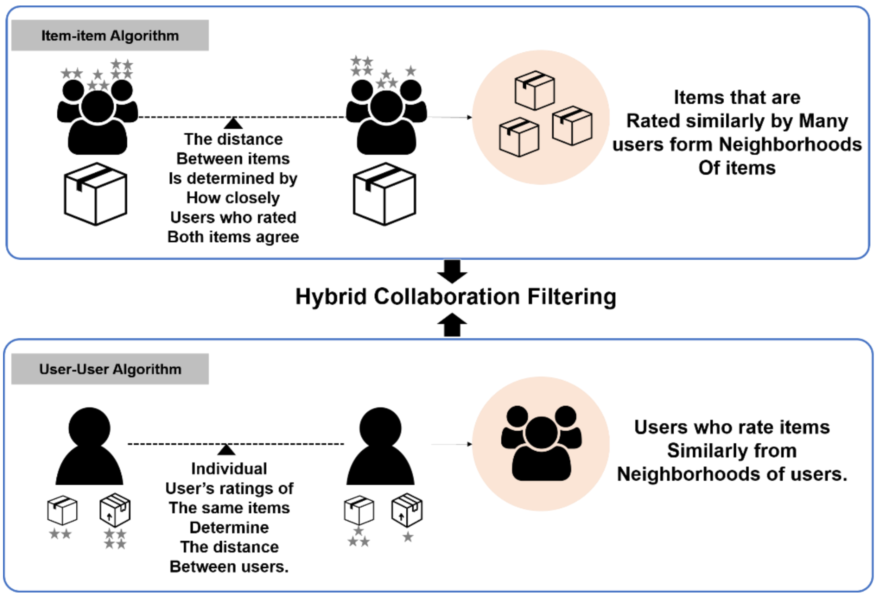

Figure 3. Process of hybrid collaboration filtering.

In Figure 3, content-based filtering is based on item–item or user–user algorithms [20]. First, the item–item algorithm [21] calculates the distance between items based on the similarity between items. Based on this distance, close items, that is, similar items are recommended. For example, if an obese user has diabetes, the distance between obesity and diabetes is determined to be very close. Therefore, it is possible to warn about the correlation between the two by recommending diabetes and obesity to an obese person and a diabetic person, respectively. Most data have fewer users than items, so various relationship data are derived based on items. This means that the more productive the data, the more accurate the recommendation.

On the other hand, the user–user algorithm [22] quantifies the distance of how much the two users' dispositions match based on common items between users. For example, if both user A and user B are diabetic, the distance between the two users is very close, 0 and the two users are determined to be very similar. However, if user A is diabetic, and user B is hyperlipidemia, the distance between the two users is far, and the similarity is also lowered. As shown above, the similarity between users is calculated to recommend items that one user and similar users like. However, the user–user algorithm is difficult to recommend if there are no similar items among users enough to calculate similarity due to lack of data. Besides, if there are items preferred by all users, the results of similarity among all users are similar, and thus the recommendation result may also be the same. In other words, there is a disadvantage that the results meaningless to recommendation are derived for the universal preference.

Recently, studies on recommendation tend to use deep learning, data mining, decision tree, and SVM. A recommendation system using deep learning assigns a weighting value to the item preferred by users for clustering and then predicts a missing value. Also, using the multi-modal deep learning model that maps a user with an item in the maximum similarity zone, a recommendation system learns the characteristics of items in a different range to expand its knowledge [23]. There is research on data mining and context-awareness technology to increase the precision of a recommendation system with the problem of user-to-item data scarcity. By utilizing context information on items effectively, it is possible to use such training sets as reviews, summaries, and overviews in case of rating data scarcity, to increase the precision of recommendation. In this way, a recommendation is made possible even if rating data is scarce in the database [24].

3. Activity Recommendation Model using Rank Correlation for Chronic Stress Management

3.1. Data Collection and Preprocessing

Concerning chronic stress data, the raw data of mental health in National Health and Nutrition Survey [25] provided by Centers for Disease Control and Prevention under the Ministry of Health and Welfare is preprocessed before use. The raw data consist of 13,248 people in total, of which the data related to mental health are used. Children under the age of 12 are not eligible for collection of mental health data. Therefore, 6547 data were extracted form 13,248 people except for no response and children. The composition of the collected data is as follows. The sex ratio consists of 3665 men and 2882 women. Age for mental health collection ranges from 12 to 80. The age distribution is evenly distributed. There are 586 people over the age of 12 and under 20, 681 people over the age of 20 and under 30, 1039 people over the age of 30 and under 40, 1089 people over the age of 40 and under 50, 1052 people over the age of 50 and under 60, 1055 people over the age of 60 and under 70 and 1045 people over the age of 70 and under 80. Also, the income quartile is classified into lower, lower and middle, upper and middle, and upper. Preprocessed data were collected at lower quartiles of 1642, lower and middle 1644, upper and middle 1631, and upper 1630. Figure 4 shows a scatter plot of the stress levels of users in the preprocessed data.

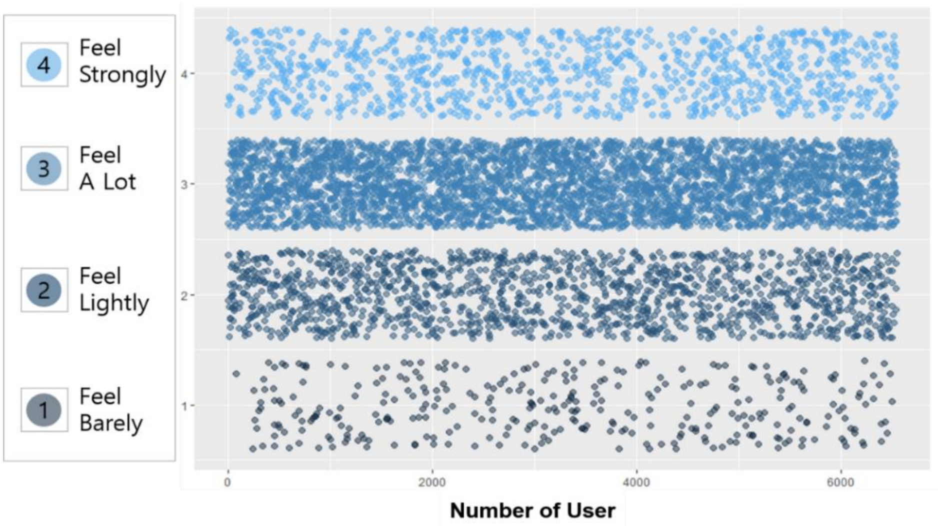

Figure 4. Scatter plot of the stress levels of users.

It shows users' stress values depending on discrete values. The value 1 means 'hardly feel', the value 2 'a little feel', the value 3 'much feel', and the value 4 'very much feel'. Of 6547 persons, only 329 hardly felt stressed, 3680 much felt stressed, and 1087 very much felt stressed. In short, of 6547 persons, 4767 or 72.8% felt stressed much. It means that in today's society, most people are chronically stressed. By looking at the trend visually, it is possible to make an intuitive prediction.

The collected mental health data consists of the result of conventional PSS (bPSS), Activity Information for Stress Management (AISM), the PSS result for activity (aPSS), and the difference between bPSS and aPSS. The AISM collected by medical information portal [26,27] is comprised of Positive Activity for Stress Management (PASM) and Negative Activity for Stress Management (NASM). PASM means stress alleviation activities, including proper exercise ($PASM_1$), leisure time ($PASM_2$), rest time ($PASM_3$), and healthy dietary habit ($PASM_4$). NASM means the activities negative to stress alleviation, such as insufficient or excess exercise ($NASM_1$), leisure time ($NASM_2$), rest time ($NASM_3$), and inappropriate dietary habits like drinking ($NASM_4$). For one month, a user gives scores ranging from 1 to 5 to activities differently depending on the intensity and frequency of $PASM_i$ or $NASM_j$. The score '1' represents the lowest intensity and frequency of activity. The score '2' means a little lower intensity and frequency of activity. The score '3' means the intermediate intensity and frequency of activity. The score '4' means a little higher intensity and frequency of activity. The score '5' represents the highest intensity and frequency of activity. For instance, if the intensity of $PASM_1$ is 3, and its frequency is 5, it means that $PASM_1$ was executed with the intermediate intensity and the highest frequency. With the use of the mean of the $PASM_i$ and $NASM_j$, the PASM and NASM values per week are calculated. The difference between bPSS and aPSS means increased or decreased stress. A positive number of differences means less stress, and a negative number means more stress.

Of the data, the example of one-week data is presented in Table 1. User1 scored 12 of bPSS, 8.35 of PASM, and 21.23 of NASM, and the user's aPSS changed to 18 after one month. It represents that the user's PSS value increased from 12 to 18, so the difference between bPSS and aPSS is −6. Therefore the user's stress increased.

Table 1. Data composition of one week. bPSS—conventional PSS; PASM— Positive Activity for Stress Management; NASM—Negative Activity for Stress Management; aPSS— the PSS result for activity.

User	bPSS	PASM	NASM	aPSS	bPSS–aPSS
1	12	8.35	21.23	18	−6
2	17	10.80	2.95	15	2
3	15	10.48	12.08	15	0
4	14	9.93	17.83	19	−5
...	...	...	...	...	...
250	15	21.85	5.90	13	2

3.2. Correlations of Perceived Stress Scale using the Rank Correlation Coefficient

With the uses of the collected data and Spearman's rank correlation coefficient [28], the correlations of the perceived stress scale are found. Spearman's rank correlation coefficient is used to find the correlations of users' S (PASM, PSS) and S (NASM, PSS). Spearman's rank correlation coefficient is the method of assigning ranks to two variables to compare and then to find their correlation. By giving a basic rank to a missing value in the calculation, it overcomes the disadvantage of Pearson's correlation coefficient [29]. A Spearman's rank correlation coefficient ranges from −1 to +1. In the case of '1', when the rank of one variable increases, that of the other variable also rises. In the case of '−1', when the rank of one variable increases, that of the other variable decreases. In the case of '0', the rank of one variable does not correlate with that of the other variable. Formula (2) presents the Spearman's rank correlation coefficient. D means the difference between the ranks of two variables, and n is the sample size. In terms of samples, there are eight attributes of PASM and eight attributes of NASM. In this study, the number of samples is 8 so that n = 8. The created correlations are presented in Table 2.

$$S(\text{AISM, PSS}) = 1 - \frac{6 \times \sum D^2}{n \times (n^2 - 1)} \quad (2)$$

In the case of User 2 in Table 2, Spearman's correlation coefficient is +0.89. It means that PASM increases, and PSS goes up. In the case of User 2, Spearman's correlation coefficient is −0.91. It means that NASM increases, and PSS decreases. In other words, PASM and NASM influence a change in the value of PSS.

Table 2. Correlation coefficient of S (PASM, PSS), S (NASM, PSS).

No.	PASM	PSS	S (PASM, PSS)	NASM	PSS	S (NASM, PSS)
1	Increased	Increased	+0.34	Increased	Decreased	−0.42
2	Increased	Decreased	+0.89	Decreased	Decreased	−0.91
3	Increased	Increased	+0.26	Increased	Not changed	−0.03
4	Decreased	Increased	+0.59	Decreased	Increased	−0.39
5	Increased	Not changed	+0.15	Increased	Not changed	−0.04
6	Decreased	Decreased	+0.41	Decreased	Decreased	−0.87
7	Not changed	Not changed	+0.06	Increased	Not changed	−0.08
8	Decreased	Increased	+0.77	Not changed	Increased	+0.02
9	Increased	Not changed	+0.09	Increased	Not changed	+0.01
10	Not changed	Increased	−0.02	Decreased	Not changed	−0.12
11	Increased	Decreased	+0.73	Increased	Decreased	−0.21
...	...	...	...	...	...	...

3.3. Activity Recommendation Model for Chronic Stress Management

The activity recommendation model for stress management employs Spearman's rank correlation coefficient to recommend a proper activity to a user through the inferred correlation. Figure 5 shows an activity recommendation model using rank correlation for chronic stress management.

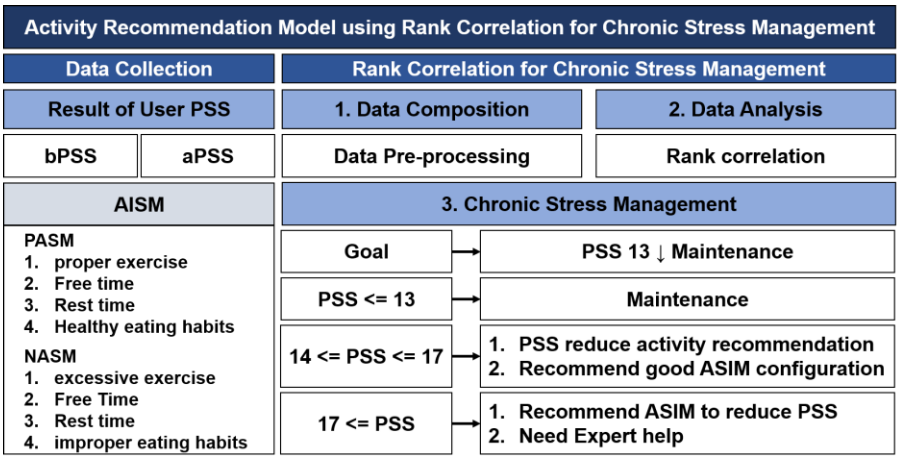

Figure 5. Activity recommendation model using rank correlation for chronic stress management.

The objective of this model is to keep a user's PSS 13 points or less. Through the change in the value of PSS, the inducement direction of AISM is determined. If a PSS value is 13 or less [6], the model recommends the activities similar to AISM and induces a further reduction in the value of PSS. If a PSS value ranges from 14 to 16 (mild stress) [8], lasting the stress long causes much exposure to Distress, and thereby the PSS value is likely to increase. Accordingly, the model recommends a user's activities that reduced a PSS value based on the user's history of records and other users' good AISM. A bPSS value ranging from 17 to 18 means moderate stress which requires cautious attention [30]. This value can easily go up if a PSS value is high. For this reason, in the intermediate step before the PSS calculation, it can exceed 19 points. Therefore, the moderate stress (PSS ranging from 17 to 18) is treated in the same way as the extremely severe stress (19), and the model finds and recommends the AISM which helped to reduce the most a PSS with the use of collaborative filtering and recommends a user to have professional help. A user who scores 17 or more of PSS at least is classified in a risk group so that the user's stress is managed in consideration of any little change in a PSS value. As such, the model recommends personalized activities by using a user's current PSS, the difference between bPSS and aPSS, and records of AISM. If there is a lack of data about a user, the model employs collaborative filtering to compare other users' records and the user's current status and to recommend the most appropriate AISM, and therefore the proposed model solves cold start problem and accomplishes precise recommendation [31,32].

4. Result and Evaluation

4.1. Activity Recommendation System for Stress Management

The method proposed in this paper was developed in an environment of Windows 10, Intel (R) Core (TM) i5-4690 CPU, and 16GB RAM. The individual's stress level is identified through the user's PSS. The PSS consists of 10 questions with weights ranging from 0 to 4. At this time, 0 means none, 1 rarely, 2 sometimes, 3 often, and 4 very often. The user selects the answer corresponding to each survey question and clicks the Check Start button, and the system sums the survey values. The sum is shown in the PSS Core Sum. Then, pressing the Diagnosis of Result button allows you to check the diagnosis of the result. The behavior guidelines are recommended to users according to the diagnosis of the result. Figure 6 shows the behavior recommendation system for stress management.

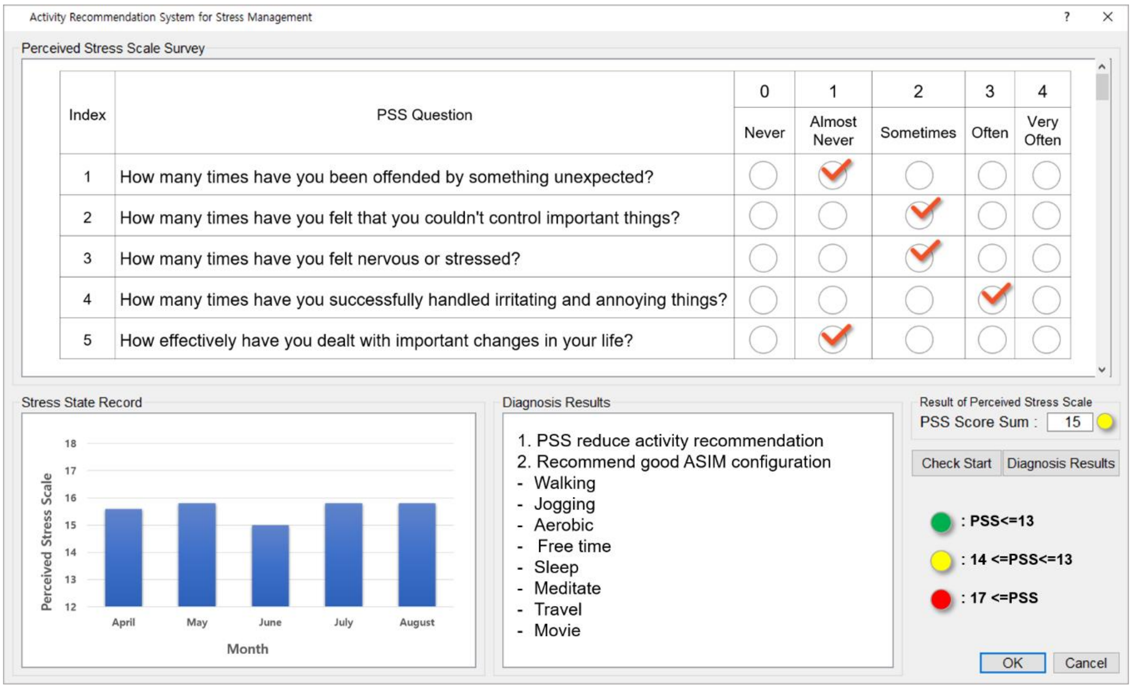

Figure 6. Activity recommendation system for stress management.

4.2. Performance Evaluation

The data for performance evaluation uses data provided by the National Health and Nutrition Survey [25]. The data of the National Health and Nutrition Survey produces statistical results for identifying health and nutritional levels, which allow people to check their health status and to manage health and prevent diseases. As the data for evaluating the performance of the proposed model, used is the pre-processed data of the National Health and Nutrition Survey. The data of 1965 persons and the data of 4582 persons are used as a test set and a training set, respectively. The model learns with the use of the training set, and its performance is repeatedly evaluated 20 persons with the use of the test set [33].

Extraneous factors of the data are removed, and modeling for statistical analysis, visualization, and causality inference are conducted to use the data in the activity recommendation model. After the proposed activity recommendation model predicts the data of the training set, its precision and recall are compared based on its recommendation results. Formula (3) presents the F-measure to compare precision and recall [34–36].

$$F - measure = \frac{2 \times Precision \times Recall}{\text{Precision} + \text{Recall}} \quad (3)$$

For the performance evaluation, the proposed Spearman Stress Management Recommendation Model (SSMRM), Pearson Recommendation Model (PRM), and Cosine Similarity Recommendation Model (CSRM) were applied to recommend the activities to reduce PSS and then their effects were compared. Table 3 shows the performance evaluation results of the activity recommendation model for the chronic stress management using SSMRM, PRM, and CSRM. It repeats the recommendation five times for 20 users and evaluates the F-measure as an average of recall and precision.

Table 3. Performance result of F-measure, recall, and precision.

User	No.	SSMRM		PRM		CSRM	
		Precision	Recall	Precision	Recall	Precision	Recall
User1	1	0.794	0.812	0.691	0.642	0.704	0.784
	2	0.817	0.777	0.737	0.658	0.718	0.785
	3	0.833	0.795	0.777	0.749	0.799	0.812
	4	0.833	0.854	0.717	0.783	0.805	0.809
	5	0.842	0.845	0.722	0.801	0.811	0.811
				… …			
User20	1	0.822	0.798	0.659	0.598	0.712	0.770
	2	0.812	0.801	0.667	0.566	0.765	0.821
	3	0.854	0.843	0.705	0.683	0.779	0.885
	4	0.898	0.888	0.704	0.702	0.812	0.891
	5	0.891	0.901	0.715	0.755	0.815	0.900
Total_average		0.846	0.891	0.751	0.792	0.792	0.817
Total_F-measure		0.868		0.771		0.804	

The table shows that as the number of recommendations to users increases, the recall, and precision increase. Besides, the results of the performance evaluation showed that the performance of the proposed SSMRM model is better than that of PRM and CSRM with the average accuracy of 0.846, recall of 0.891 and F-measure of 0.868. SSMRM uses rank rather than directly using observations through the Spearman correlation analysis and improved the accuracy by solving the missing value problem by substituting the default rank value if missing or inaccurate. As a result, more accurate relationships than PRM using Pearson's correlation analysis and CSRM using cosine similarity were found, enabling the recommendation of appropriate stress management activities to users.

5. Discussion

The proposed method finds the correlation between PSAM, NSAM, and PSS with the use of Spearman's correlation coefficient, and recommends an activity to reduce PSS with the use of a correlation coefficient. When a correlation coefficient is drawn, the error of the missing value in a training set is reduced with the use of the Spearman's correlation coefficient-based ranks. Therefore, Spearman's correlation analysis solves the problem of Pearson's correlation analysis that fails to draw a result if there is a missing value and can precisely infer a correlation coefficient for the new data not found in a training data since it employs a basic value. Also, Spearman's correlation analysis solves the problem of underfitting that occurs due to a missing value in a training set. A Spearman's rank correlation coefficient ranges from −1 to +1. In case of a coefficient closer to '+1', when the rank of one variable increases, that of the other variable also rises. In case of a coefficient closer to '−1', when the rank of one variable increases, that of the other variable decreases. In the case of '0', the rank of one variable does not correlate with that of the other variable. With the use of Spearman's correlation coefficient, the proposed model recommends a user the AISM that consists of PSAM whose coefficient is closer to +1 and NSAM whose coefficient is closer to −1. It also solves the cold start problem that can occur due to a lack of a user's data.

6. Conclusions

In this paper, the activity recommendation model using rank correlation has been developed to manage user's chronic stress. The proposed model continuously tracks the user's perception indicator, the Perceived Stress Scale (PSS). The model reasons the correlation between the tracked PSS and the Activity Information for Stress Management (AISM) that affect it. This allows users to manage chronic stress by recommending appropriate ASIM to users. Using collaborative recommendations that refer to other users' data, the system recommends the positive AISM of other users most similar to the user. In this way, it is possible to make a variety of precise recommendations. By employing the proposed model, users can manage their PSS efficiently and reduce chronic stress effectively. You can also keep track of one's PSS and see how his or her stress changes appear. Besides, the correlation coefficient shows whether or not an activity has a significant effect on one's stress. It will also help avoid risky choices by inducing professional help right away when the PSS is moderate or extreme stress with a score of 17 or higher. With chronic stress emerging as a big issue in modern society, we need to manage stress appropriately. If we use the model we propose effectively, we can overcome their stress. We can improve our quality of life by reducing negative stimuli to distress and using positive exposure to Eustress.

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