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Research paper

Developing a model to predict the Social Activity Participation of the senior citizens living in South Korea by Combining Artificial Neural Network and QUEST Algorithm

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Abstract

Social participation in old age is important in terms of the quality of life. The objectives of this study were to establish a statistical classification model, which can predict the social participation in the old age and provide baseline data for achieving successful aging by using a dataset representing South Korea and combining artificial neural network with QUEST algorithm. This study analyzed the data of 1,864 subjects (829 males and 1,035 females) who were equal to or older than 65 years and completed the 2015 Community Health Survey. The dependent variable was the social activities within the past one month (yes/no). The factors associated with the social participation in the old age were analyzed by using the neural network and QUEST algorithm. Among 1,864 subjects, 1,035 senior citizens (55.5%) did not have social activities during the past one month. The results of established QUEST algorithm classification model revealed that subjective health, age, the frequency of meeting a neighbor, the frequency of meeting a relative, the highest level of education, and walking per week were significant classification variables. Among them, subjective health status was a predictive factor associated with it first. The results of the developed model revealed that social care and institutional measures are needed to promote the social participation of the elderly for achieving the successful aging of the aging society.

Keywords: *social activities, quality of life, subjective health status, neural network, decision tree model*

1. Introduction

As South Korean entering in an aging society, more healthy elderly people have the will to work in South Korea. As of 2018, the average life expectancy of South Korean is estimated to be 78.9 years for males and 85.4 years for females [1]. It is expected that the life expectancy will be improved owing to the advancement of medical technology and better nutritive conditions. It is also believed that the health of the elderly will be improved in the future. On the other hand, the elderly do not have many social activity opportunities, even though they are still healthy and have the will and capability to work. Therefore, the life of the elderly is vulnerable in terms of economic and emotional aspects [2].

Old age is the last cycle of the life. If the elderly can develop themselves through continuous social participation, they will be able to lead a satisfying and successful life [3]. The social participation includes activities that are planned before old age in advance and advanced further, those newly initiating, continuous self-improvement, and newly identified hobby or specialty. Nonetheless, the main goal of the elderly health policy is limited to health behavior or the adaptation to old age so far [4]. The promotion of social participation and development in old age is still insufficient.

Previous studies on the social participation of the elderly argued that social participation includes productive activities such as the economic activity and non-productive activities such as leisure activities [2, 5]. In other words, social participation is defined as valuable activities that contribute to the society or activities that produce goods and services with having economic values [6].

Social participation in old age is important in terms of the quality of life. Social activities create relationships with people nearby and consistently maintain the contact with a society. It also promotes personal satisfaction and positively affects the successful aging. Ultimately, it enhances the quality of an individual's life [7]. The leisure activities of the elderly help the elderly have satisfying lives physically and emotionally [8], are the means to interact with others because they can have diverse experiences and opportunities in a local society, enhance the health of the elderly ultimately [9], and provide psychological stability and life satisfaction through active leisure activities [10]. In summary, the social participation in old age can improve the physical and mental health and promote the satisfaction of life by providing the opportunities of social interaction. Consequently, the elderly can achieve the successful aging through them.

Successful aging focuses on the physical, psychological, and social adaptation and roles that are formed in the old age [11]. Particularly, it is related to diverse social activities [11]. Previous studies have shown that the elderly experienced better satisfaction in life when they had a higher frequency of social participation [9, 12]. It is necessary to identify the factors associated with the social participation in the old

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age in order to improve the quality of life in the old age and achieve successful aging. Particularly, it is needed to establish a prediction model that can explain the path between risk factors or a compound factor in order to precisely identify the characteristics of social participation in the old age because multidimensional factors such as environmental, individual, and economic factors are associated with social participation. Nevertheless, the majority of the elderly in South Korea is mainly interested in economic activities such as employment. Therefore, only a few studies have evaluated the factors influencing the participation in social activities including health behaviors, demographic characteristics, and environmental factors.

The artificial neural network has been used as a research tool for exploring factors in recent years. The artificial neural network can analyze categorical variables as well as continuous variables. Moreover, it can cope with the noise of data by employing a fault-tolerant system, does not have statistical assumptions, and it can handle non-linearity issues, which are merits of it [13, 14]. The objectives of this study were to establish a statistical classification model, which can predict the social participation in the old age and provide baseline data for achieving successful aging by using a dataset representing South Korea and combining artificial neural network with QUEST algorithm.

2. Methods and Materials

2.1. Subjects

This study analyzed the raw data of 2015 Community Health Survey, which was conducted between Aug 31 and Nov 8, 2015, by Korea Centers for Disease Control and Prevention in cooperation with 254 public health centers and 35 universities. Community Health Survey was carried out to establish the basis for conducting evidence-based health projects and produce local health statistics [15]. The survey items consisted of health behaviors, medical use, quality of life, and economic activities. The survey was conducted by computer assisted personal interviewing (CAPI), which is 1:1 interview method assisted by a laptop and a trained surveyor visited a house in person. This study analyzed the data of 1,864 subjects (829 males and 1,035 females) who were equal to or older than 65 years and completed the health and household surveys.

2.2. Measurement and Definitions of Variables

The dependent variable was the social activities within the past one month (yes/no). Explanatory variables included age (i.e., 65-74 years old and 75 years or older), gender, the highest level of education (i.e., below elementary school, middle school, high school, and equal to or higher than university graduation), current employment status (i.e., employment and unemployment), monthly mean total household income (i.e., <2 million KRW, 2 million KRW≤ and <4 million KRW, and 4 million KRW≤), marital status (i.e., living with a spouse, married but not living with a spouse, and not married), drinking frequency (i.e., less than once a week and more than once), smoking (i.e., smoking and non-smoking), subjective health status (i.e., good, normal, and bad), walking per week (i.e., equal to or more than two days and less than one day), depression experience in the past one year (i.e., yes and no), disease or accident experience in the past two weeks (i.e., yes and no), subjective stress level (i.e., yes and no), the frequency of meeting a neighbor (i.e., less than once a month and more than twice a month), and frequency meeting a relative (i.e., less than once a month and more than twice a month).

2.3. Artificial Neural Network Analysis

2.3.1. Artificial Neural Network Analysis

The factors associated with the social participation in the old age were analyzed by using the neural network. The artificial neural network is a parallel computational model that represents knowledge and process information in parallel like the human brain [17]. It is a nonlinear model that is used to solve a prediction problem in complex structured data [17]. The structure of the neural network is similar to that of human neurons. The basic nodes called artificial neurons play the same role as neurons and they are connected to each other to form a neural network (Fig. 1). An artificial neural network is composed of an input layer, which is an input variable, and a hidden layer, which is composed of hidden nodes. Hidden nodes process the linear combination of variables, which are delivered from the input layer, into a non-linear layer and deliver it to an output layer or another hidden layer [18]. This study used the radial basis function (RBF) neural network that uses RBF as a coupling function of a hidden layer. RBF is as the same as Eq. (1).

$$H_i = \exp\left(-\frac{(x_1-c_{1i})^2+(x_2-c_{2i})^2+\cdots+(x_k-c_{ki})^2}{r_i^2}\right) \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (1)$$

In the artificial neuron network analysis, a variable, which has a relative importance of inputs equal to or greater than 0.1, was considered as a main explanatory variable affecting the decision of dependent variable and it was included in the decision tree model.

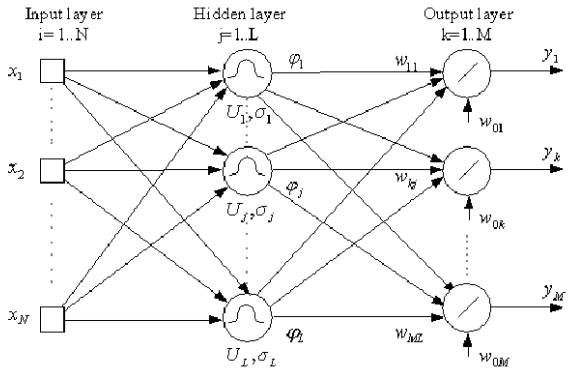


Fig. 1: Algorithm of artificial neural network [16]

2.3.2. QUEST Algorithm

QUEST is an algorithm that selects significant variables among the initial input variables, conducts a secondary discrimination analysis based on the selected variables, and chooses predictive variables in order to reduce the variable selection bias (Fig. 2). A variable with the least probability was selected as a classification variable by using ANOVA F-statistics for continuous variables and chi-square test for categorical variables [9]. Finally, the secondary discrimination analysis was conducted and the classification point was selected for classification variables chosen from this process [20].

In QUEST algorithm, when data are composed of categorical variables and a dependent variable has more than three categories, two-mean cluster analysis was performed. In this case, a second-order discriminant analysis was used and a child node was formed by finding an explanatory variable that classifies the dependent variable the best. This study converted all explanatory variables including dependent variables into categorical variables and analyzed them in order to reduce the bias of QUEST algorithm as much as possible [21].

In the model of this study, the separation and merge criterion of the decision rule for QUEST algorithm was set to 0.05. Moreover, the number of parent nodes was limited to 250, the number of child nodes was limited to 150, and the number of branches was limited to 4. The validity of the model was tested using a 10-fold cross-validation test and the risk results of each model were compared.

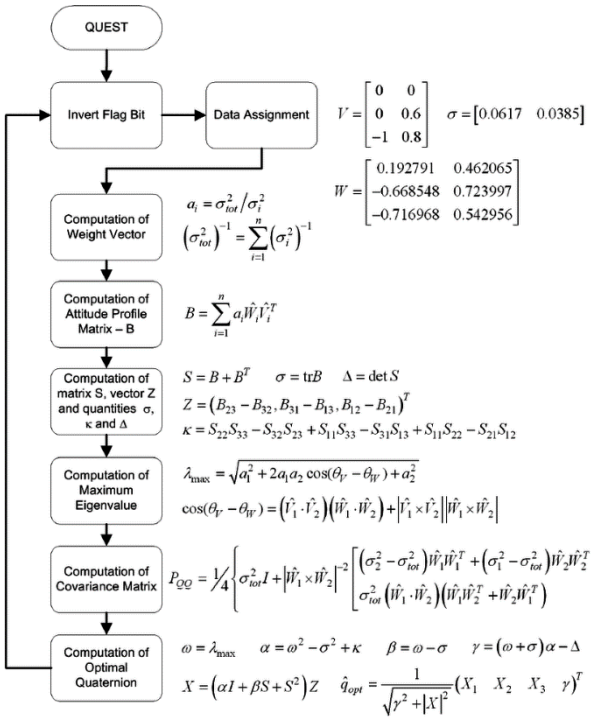


Fig. 2: Algorithm of QUEST model [19]

3. Results

3.1. General Characteristics of Subjects

Among 1,864 subjects, 1,035 senior citizens (55.5%) did not have social activities during the past one month Table 1. The results of the Chi-square test showed that the elderly who experienced at least one social activity and the elderly who did not experience a social activity were significantly ($p<0.05$) different in age, gender, the highest level of education, current employment status, monthly mean total household income, marital status, drinking frequency, subjective health status, walking per week, depression experience in the past one year,

disease or accident experience in the past two weeks, the frequency of meeting a neighbor, and frequency meeting a relative. The ratio of no social activity experience was high when subjects were equal to or older than 75 years (60.1), female (48.5%), below elementary school (55.9), unemployed (48.1%), monthly mean total household income less than 2 million KRW (51.8%), separation by death (68.8%), drinking less than once a week (47.2%), bad subjective health status (60.6%), walking less than once a week (70.6%), experienced depression in the past one year (60.1%), experienced disease or accident in the past two weeks (51.8%), the frequency of meeting a neighbor less than once a month (56.8%), and frequency meeting a relative less than once a month (59.2%).

3.2. Exploring Social Participation Factors in the Old Age using Artificial Neural Network Analysis

Artificial neural network analysis was conducted for 1,133 learning samples (62.9%), 496 test samples (27.5%), and 172 validation samples (9.6%) and the study derived nine hidden layers, which created the test data error the least. Moreover, it was found that the sum of squared error was 240.11, while the classification accuracies of learning sample, test sample, and validation sample were 75.8, 72.8, and 75.0%, respectively. AUROC was 0.718. The fitness and explanatory power of the classification model were more than average [Fig. 3].

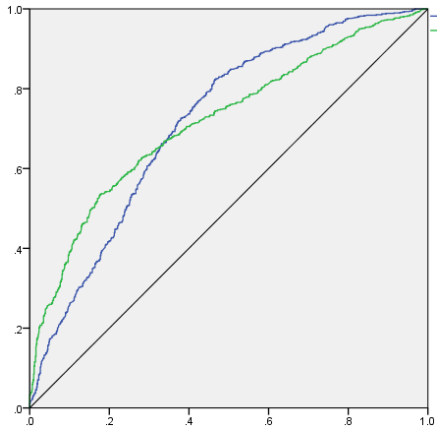


Fig. 3: ROC curve area for final model

Fig. 4 shows the results of the synaptic weighted network diagram, which established a RBF neural network model. In this model, subjective health status, age, household income, depression, the frequency of meeting a neighbor, walking per week, disease or accident experience in the past two weeks, and the highest level of education were assumed as major variables with high social participation weights. The normalized importance, which makes the units of input variable importance and input variables into the same unit by an influence category, is presented in Table 2 and Fig. 5.

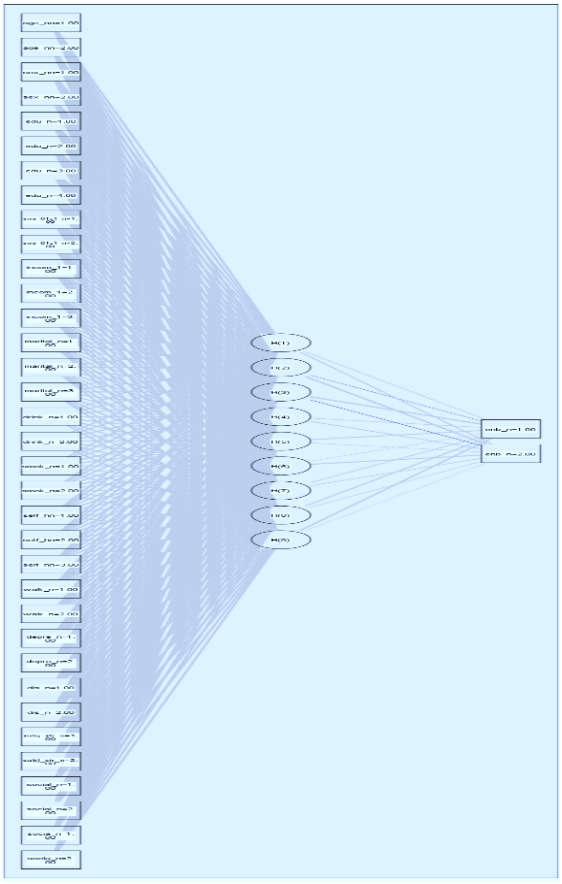


Fig. 4: Synaptic weighted network diagram

Table 1: General Characteristics of Subjects, n (%)

Variables	Social activities within the past one month		p
	Yes (n=1,020)	No (n=844)	
Age			<0.001
65-74	784 (61.6)	489 (38.4)	
75+	236 (39.9)	355 (60.1)	
Gender			0.002
Male	487 (58.7)	342 (41.3)	
Female	533 (51.5)	502 (48.5)	
Education			<0.001
Below elementary school	335 (44.1)	424 (55.9)	
Middle school	191 (55.8)	151 (44.2)	
High school	290 (61.8)	179 (38.2)	
Equal to or higher than university graduation	199 (69.6)	87 (30.4)	
Current employment status			<0.001
Employment	284 (63.5)	163 (36.5)	
Unemployment	736 (51.9)	681 (48.1)	
Monthly mean total household income			<0.001
<2 million KRW	526 (48.2)	566 (51.8)	
2-4 million KRW	289 (63.2)	168 (36.8)	
4 million KRW≤	184 (65.2)	98 (34.8)	
Marital status			<0.001
Living with a spouse	762 (60.2)	504 (39.8)	
Married but not living with a spouse	252 (43.4)	329 (56.6)	
Not married	5 (31.3)	11 (68.8)	
Drinking frequency			<0.001
Less than once a week	830 (52.8)	742 (47.2)	
More than once	189 (65.2)	101 (34.8)	
Smoking			0.320
Current smoker	89 (51.1)	85 (48.9)	
Nonsmoker	931 (55.1)	759 (44.9)	
Subjective health status			<0.001
Good	334 (63.7)	190 (36.3)	
Normal,	432 (62.2)	263 (37.8)	
Bad	254 (39.4)	391 (60.6)	
Walking per week			<0.001
Equal to or more than two days	955 (58.1)	688 (41.9)	
Less than one day	65 (29.4)	156 (70.6)	
Depression experience in the past one year			<0.001
Yes	65 (39.9)	98 (60.1)	
No	954 (56.1)	746 (43.9)	
Disease or accident experience in the past two weeks			0.012
Yes	149 (48.2)	160 (51.8)	
No	870 (56.0)	683 (44.0)	
Subjective stress level			0.196
Yes	661 (53.7)	571 (46.3)	
No	359 (56.8)	273 (43.2)	
Frequency of meeting a neighbor			<0.001
Less than once a month	266 (43.2)	350 (56.8)	
More than twice a month	747 (60.9)	480 (39.1)	
Frequency meeting a relative			<0.001
Less than once a month	151 (40.8)	219 (59.2)	
More than twice a month	868 (58.2)	623 (41.8)	

Table 2: Relative importance of inputs

Inputs	Relative importance	Normalized importance
Age	0.106	89.2%
gender	0.057	47.7%
education	0.069	57.8%
current employment status	0.052	44.0%
monthly mean total household income	0.094	79.2%
marital status	0.043	36.1%
drinking frequency	0.035	29.8%
smoking	0.024	20.2%
subjective health status	0.119	100.0%
walking per week	0.076	63.9%
depression experience in the past one year	0.087	73.5%
disease or accident experience in the past two weeks	0.073	61.5%
subjective stress level	0.057	47.8%

the frequency of meeting a neighbor	0.076	64.1%
frequency meeting a relative	0.031	25.7%

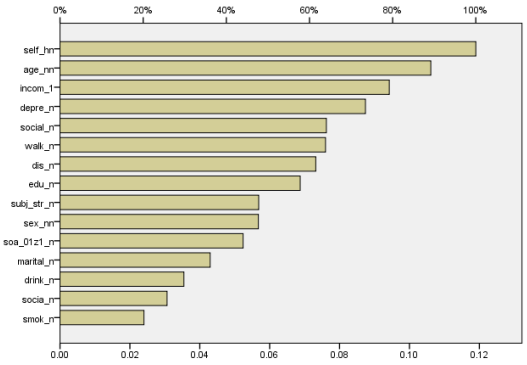


Fig. 5: Normalized importance of inputs

3.3. Social Participation Prediction Model in Old Age by Using QUEST Algorithm

The social participation prediction model in the old age using the QUEST algorithm is shown in Fig. 6. The results of established QUEST algorithm classification model revealed that subjective health, age, the frequency of meeting a neighbor, the frequency of meeting a relative, the highest level of education, and walking per week were significant classification variables. Among them, subjective health status was a predictive factor associated with it first.

Table 3 shows the profit graph of the social participation prediction model in the old age using the QUEST algorithm. Five nodes were identified as meaningful paths that effectively predicted social participation. The path 1 with the largest profit index is the elderly who met a neighbor less than once a month, were in poor subjective health status, and had the highest level education of middle school. The majority of them (86%) responded that they did not have a social participation experience in the past one month. The profit index was 191.0%. The elderly of the path 2 were who were in poor health status, met a neighbor more than twice a month, and walked less than once a week. The 75.7% of them responded that they did not have social participation for the past one month. The profit index of this path was 167.1%. The path 3 were the elderly who met a neighbor less than once a month and were equal to or older than 75. The 62.2% of them responded that they did not participate in social activities in the past one month. The profit index of this path was 137.3%. The elderly of the path 4 were people who had normal subjective health status, met a neighbor or a relative less than once a month, and were between 65 and 75 years old. The 61.6% of them indicated that they experienced depression. The profit index of this path was 136.1%. The path 5 was the elderly who were in poor subjective health status, met a neighbor less than once a month, and graduated from high school. The 59.5% of them said that they did not participate in social activities in the past one month. The profit index was 131.5%.

The results of the 10-fold cross-validation test showed that the prediction accuracy of the model was 75.4%. The risk index of cross-classification model, the misclassification rate, and the standard error were 0.348, 34.8%, and 0.01. They were identical to the risk index (0.347), the misclassification rate (34.7%), and the standard error (0.011) of the prediction model.

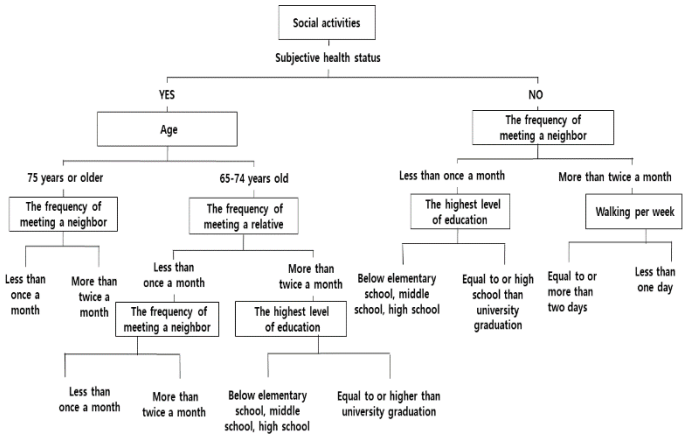


Fig. 6: The social participation prediction model in the old age using the QUEST algorithm

4. Discussion

The social participation in the old age is important for successful aging. This study constructed a social participation prediction model for senior citizens living in South Korea. The results of this study showed that subjective health status, age, the frequency of meeting a neighbor, the frequency of meeting a relative, the highest level of education, and walking were significant variables. Among them, the subjective health status was the predictive factor associated with it by priority. The results of this study were similar to the results of a previous study, which reported that the subjective health status was closely related with the social participation [22].

The self-assessed subjective health is to define own health and measure own health. Therefore, it is known to reflect the overall health status of the elderly [23]. Although the subjective health status varies from person to person, it is the most fundamental factor for assessing social activities and the core element of successful aging [23]. Similar to the results of this study, a number of previous studies reported that the social participation and the quality of life were enhanced when the subjective health status was better [10].

A regular contact with a neighbor or a relative was a major predictor of social participation. The possibility of social participation was higher when there were more social contacts with neighbors. On the

Table 3: Gains chart of predictor variable by QUEST algorithm

Nodeno	Node n(%)[1]	Gain n(%)[2]	Response%[3]	Gain Index%[4]	Characteristics
11	133 (7.1)	115 (13.6)	86.5	191.0	The elderly who met a neighbor less than once a month, were in poor subjective health status, and had the highest level education of middle school
14	74 (4.0)	56 (6.6)	75.7	167.1	The elderly who were in poor health status, met a neighbor more than twice a month, and walked less than once a week
7	111 (6.0)	69 (8.2)	62.2	137.3	The elderly who met a neighbor less than once a month and were equal to or older than 75years old
15	73 (3.9)	45 (5.3)	61.6	136.1	The elderly of the path 4 were people who had normal subjective health status, met a neighbor or a relative less than once a month, and were between 65 and 75 years old
12	84 (4.5)	50 (5.9)	59.5	131.5	The elderly who were in poor subjective health status, met a neighbor less than once a month, and graduated from high school

[1] Node n(%); node number, % to 1,864
[2] Gain n(%); gain number, % to 844
[3] Response (%): The fraction of the social activities in subjects
[4] Gain index (%):=191.0 in total 18 node

other hand, the possibility of social participation was lower when the contact with a friend or a neighbor was lower. Previous study showed that the social contact relationship with others (e.g., a friend, a relative, and a neighbor) and the social contact with others were major factors for achieving successful aging [24, 25], which agreed with the results of this study. It was noteworthy that the regular contact with people was more important than the size of a friendship. Therefore, the results of this study suggested that a social support is needed to increase the number of contact with a neighbor or a relative in order to increase the social participation in the old age.

The highest level of education was also a predictor of the social participation in the old age. It is believed that education level had positive effects on social participation because the higher education level tended to increase the socioeconomic status and it could comfort people psychologically.

On the other hand, the economic activity and income level of the elderly were not major predictors of social participation. Nonetheless, South Korea has continuously invested in the employment and lifelong education for securing stable income by improving the quality of labor as a means to increase the social participation of the elderly and it has been considered as the welfare of the elderly [26]. The basic security can secure the quality of life in the old age. Therefore, it is important to promote a social environment that the elderly can maintain good health and continue economic activities. However, the basic security does not necessarily promote social participation or create an active aging culture. Therefore, it is urgent to establish policies that can expand the social network in order to promote the social participation of the elderly.

The results of the developed model revealed that social care and institutional measures are needed to promote the social participation of the elderly for achieving the successful aging of the aging society.

Conclusion

This study constructed a social participation prediction model using a data mining for senior citizens living in South Korea. The results of the developed model revealed that social care and institutional measures are needed to promote the social participation of the elderly for achieving the successful aging of the aging society. In the future, it will be necessary to find a way to increase the predictability of outcome variables using deep learning models such as Convolutional Neural Network.

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