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Factors influencing quality of life among the elderly: An approach using logistic regression

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Abstract:

BACKGROUND: Improving the physical, psychological, and social factors in the elderly significantly increases the QoL[1] among them. This study aims to identify the crucial factors for predicting QoL among the elderly using statistical methods.

MATERIALS AND METHODS: In this study, 980 samples related to the elderly with favorable and unfavorable QoL were investigated. The elderly's QoL was investigated using a qualitative and self-assessment questionnaire that measured the QoL among them by five Likert spectrum and independent factors. The Chi-square test and eta coefficient were used to determine the relationship between each predicting factor of the elderly's QoL in SPSS V 25 software. Finally, we used the Enter and Forward LR methods to determine the correlation of influential factors in the presence of other variables.

RESULTS: The study showed that 20 variables gained a significant relationship with the quality of life of the elderly at $P < 0.05$. The study results showed that the degree of dependence ($P = 0.03$), diabetes mellitus ($P = 0.03$), formal and informal social relationships ($P = 0.01$ and $P = 0.02$), ability to play an emotional role ($P = 0.03$), physical performance ($P = 0.01$), heart diseases and arterial blood pressure ($P = 0.02$), and cancer ($P = 0.01$) have favorable predictive power in predicting the QoL among the elderly.

CONCLUSION: Attempts to identify and modify the important factors affecting the elderly's QoL have a significant role in improving the QoL and life satisfaction in this age group people. This study showed that the statistical methods have a pleasant capability to discover the factors associated with the elderly's QoL with high performance in this regard.

Keywords:

Elderly, factor analysis, quality of life, statistical regression

Introduction

Due to scientific promotions in healthcare and reduced mortality in the global population, aging has become an increasing phenomenon.[1-3] This phenomenon refers to a period of human life in which people's physical and cognitive abilities will decrease, so the social constraints and dependence on other persons would be increased.[4,5] According to the reports generated by World Health Organization (WHO) and the Organization for Economic Cooperation and Development (OECD), age over 65 years old is considered the beginning of the old age period.[6] Recent studies have demonstrated that the increase in the elderly population has occurred globally, and it's estimated to exceed two billion by 2050.[7] The results of the United Nations (UN) demographic data analysis have shown that by 2050, about 22% of Iran's population will be over 65 years old.[8] The negative consequences of the growth in elderly population numbers can be mentioned as the increase in physical diseases and the complications and ailments associated with them, the increase in mental

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diseases such as the increase in depression, worry, anxiety, and the increase in the amount of dependence on others in doing daily tasks. It consequently leads to a decrease in the QoL among the elderly.[9] Also, the need of this age group for hospital services would be increased. Therefore, it will impose economic costs on the individual and the society associated with older adults.[10] In this age group, the rate of chronic and devastating diseases such as high blood pressure, diabetes, heart diseases, Alzheimer's, stroke, and all types of cancers increases. Therefore, it is essential to pay attention to this period of the elderly's life.[11,12] The QoL among the elderly is a multidimensional concept associated with the physical health, mental health, and environmental and social abilities of elderlies.[13] Advancing the QoL among the elderly is crucial; however, behaviors that improve health and QoL in them are important issues that have not been considered much in today's societies. Assessing the QoL among the elderly in clinical settings leads to closer cooperation between physicians, patients, and other care providers, increasing patients' awareness of their diseases and health status, familiarizing them with the importance of various treatment plans, and selecting the best ones for themselves.[14] So far, Machine Learning (ML) techniques and statistical methods have a significant role in identifying effective factors influencing various situations, including health conditions such as various diseases.[15-19] Previous studies have shown that statistical tools and techniques significantly analyze data on QoL among the elderly.[20-22] Early recognition of factors influencing the quality of life among the elderly will lead to better modification of the physical and psychological factors and the acceptable level of their participation in society.[23-25] In the previous studies, the physical and mental factors were analyzed for the elderly's QoL and social factors were given less attention. The social factors are crucial in predicting the QoL among the elderly and identifying the factors affecting the elderly's QoL and trying to modify and enhance these factors among the elderly in addition to the physical and mental factors can increase the QoL and life satisfaction in the latest duration of people lives.[26-29] In this study, contrary to the previous studies performed regarding the factor analysis affecting the elderly's QoL, we investigated more social factors in addition to physical and mental factors to get a better model predicting the QoL among the elderly and determine the best factor influencing the QoL among the elderly with model performance betterment and higher generalizability. Therefore, this work aims to identify and analyze the factors affecting the QoL among the elderly through physical, mental, and social factors affecting it.

Methods

Study design and setting

In this retrospective, descriptive, and analytical study, the research community was older people over 65 years in residence of three elderly centers in Ahvaz city named Hamdali, Hasti, and Mehrjovian. All the health records available in those elderly centers whose information was stored in one unified dataset were investigated in this study.

Study participants and sampling

In this study, we used 631 samples related to the unfavorable quality of life and 349 cases belonging to the favorable QoL stored in one dataset. The independent variables in the three main categories were physical diseases, mental diseases, social indicators, and demographic characteristics of the elderly. In this research, the dependent variable was the QoL among the elderly with a two-valued class. All factors affecting QoL among the elderly are shown in Table 1.

Data collection tool and technique

Quality of life in the elderly is the output variable. It can be obtained by five Likert scales responding to the question, how do you evaluate the quality of your life? The responses to those five Likert spectrums include "very bad", "bad", "moderate", "good" and "very good". It was a self-assessment and qualitative approach and the elderly responded to one of the spectrums defined by Likert. To reduce the class numbers for more convenience analysis, it's converted into two groups, "unfavorable" and "favorable," by gerontologists and registered in the database. The data were checked in terms of quantity and quality, and proportionality to perform statistical analysis. The data with missing values of more than 5%, or noisy or redundant were removed from the database. To replace the missing values of less than 5%, the K Nearest Neighbor (KNN) algorithm was used in the Rapid miner software environment. The relationship of each independent predictor with the QoL among the elderly as the output class was investigated through the Pearson Chi-square test (formula 1) and eta correlation coefficient. P <0.05 was considered in this regard. After identifying the effective variables related to the elderly's, the binary logistic regression method was used as a univariate technique to get the most important factors influencing the QoL among the elderly. To this end, two BLR methods of the Forward LR and Enter were investigated simultaneously. In the Forward LR method, each variable affecting the QoL among the elderly is entered into the model separately. If they significantly correlate with QoL among the elderly, they will be entered into the model at different steps. In the Enter method, all variables are entered into the regression model in one step. The statistical level $P < 0.05$ was used to determine the significance of the relationship of each input variable to QoL among the elderly. The performance of each logistic regression model in predicting the QoL among the elderly was

Table 1: All factors affecting the elderly's QoL

Factors	Values of factor	Frequency of factors (MeanSD)	Role
Age	-	75.36.6	Input
gender	Male (0), Female (1)	Male (452), Female (528)	Input
Education status	Illiterate (0), Elementary (1) Diploma (2), Academic (3)	Illiterate (560), Elementary (380) Diploma (35), Academic (5)	Input
Marital Status	Single (0), married (1), divorced (2), widowed (3)	Single (654), married (68), divorced (52), widowed (206)	Input
Place of residence	Urban (1), Rural (0)	Urban (625), Rural (355)	Input
Heart diseases and arterial blood pressure	Yes (1), No (0)	Yes (324), No (626)	Input
Musculoskeletal diseases	Yes (1), No (0)	Yes (122), No (858)	Input
Diabetes Mellitus	Yes (1), No (0)	Yes (378), No (602)	Input
Digestive diseases	Yes (1), No (0)	Yes (58), No (922)	Input
Respiratory diseases	Yes (1), No (0)	Yes (124), No (656)	Input
Nervous diseases	Yes (1), No (0)	Yes (144), No (826)	Input
Cancer	Yes (1), No (0)	Yes (58), No (922)	Input
Mental disabilities	Yes (1), No (0)	Yes (375), No (605)	Input
Visual disabilities	Yes (1), No (0)	Yes (210), No (770)	Input
Hearing disabilities	Yes (1), No (0)	Yes (385), No (595)	Input
Skin diseases	Yes (1), No (0)	Yes (113), No (867)	Input
Other diseases	Yes (1), No (0)	Yes (124), No (856)	Input
The degree of dependence	Very High (1), High (2), Moderate (3), Low (4), Very Low (5)	Very High (175), High (326), Moderate (318), Low (122), Very Low (39)	Input
Physical performance	Favorable (1), Unfavorable (0)	Favorable (565), Unfavorable (415)	Input
Physical pain	Yes (1), No (0)	Yes (458), No (522)	Input
Perceived health condition	Bad (0), Moderate (1), Good (2)	Bad (57), Moderate (573), Good (350)	Input
The capability of emotional role	Yes (1), No (0)	Yes (342), No (648)	Input
Positive state index	None (0), Low (1), High (2)	None (386), Low (443), High (151)	Input
Negative state index	None (0), Low (1), High (2)	None (130), Low (287), High (563)	Input
Formal social relationships	Never (0), One or two times/year (1), One or two times/month (2), One or two times/week (3), Every day (4)	Never (127), One or two times/year (325), One or two times/month (271), One or two times/week (196), Every day (61)	Input
Informal social relationships	Never (0), One or two times/year (1), One or two times/month (2), One or two times/week (3), Every day (4)	Never (55), One or two times/year (145), One or two times/month (478), One or two times/week (272), Every day (30)	Input
General health	Yes (1), No (0)	Yes (725), No (255)	Input
hilarity	Yes (1), No (0)	Yes (589), No (391)	Input
Quality of life	Favorable (0), Unfavorable (1)	Favorable (349), Unfavorable (631)	Target

measured using different performance matrices, including sensitivity (formula 2), specificity (formula 3), accuracy (formula 4), F measure (formula 5), and AUC. The models were examined in training and testing situations for overfitting investigation. Based on hold-out performance validation. 70% of the data was used to train the model, and 30% was used for testing. Finally, the performance of two BLR models was evaluated to investigate the predictive strength of factors influencing the QoL among the elderly.

$$\text{Formula 1: } x^2 = \sum_{i=1}^{n} \frac{(\text{Oi} - \text{Ei})^2}{\text{Ei}}$$

$$\text{Formula 2: Sensitivity} = \frac{\text{TP}}{\text{TP} + \text{FN}}$$

$$\text{Formula 3: Specificity} = \frac{\text{TN}}{\text{TN} + \text{FP}}$$

$$\text{Formula 4: Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{FN} + \text{FP} + \text{TN}}$$

$$\text{Formula 5: F} - \text{measure} = \frac{2\text{*Sensitivity*Specificity}}{\text{Sensitivity} + \text{Specificity}}$$

Ethical consideration

The ethical committee of the Iran University of Medical Sciences approved this study as a research project with the ethical code of IR.IUMS.REC.1401.780.

Results

By removing records with more than 5% missing values, and noisy, and aggregated data, the five samples belonging to QoL and non-QoL elderly cases were removed from the study. The lost data of 67 cases with less than 5% missing values were replaced by the KNN algorithm method with specific amounts of K = 1,3,5. The results of Pearson's Chi-square analysis and eta correlation coefficient in determining the relationship between each input variable and QoL among the elderly are shown in Table 2.

Based on the information given form Table 2, age (Eta = 0.61), heart diseases and arterial blood pressure ($P = 0.03$), musculoskeletal diseases ($P = 0.02$), diabetes mellitus ($P = 0.03$), respiratory diseases such as asthma ($P = 0.03$), cancer diseases ($P = 0.04$), mental disability ($P = 0.02$), hearing disability ($P = 0.01$), visual disability ($P = 0.01$), the degree of dependence ($P = 0.01$), physical performance ($P = 0.04$), physical pain ($P = 0.03$), perceived health condition ($P = 0.01$), capability to the emotional role ($P = 0.02$), positive state index ($P = 0.01$), negative state index ($P = 0.01$), formal social relationships ($P = 0.01$), general health ($P = 0.03$), informal social relationships ($P = 0.02$) and hilarity ($P = 0.03$) have a significant relationship with the QoL among the elderly at the statistical level of $P < 0.05$ and the coefficient of eta above 0.4. The variables of gender, marital status, education status, place of residence, digestive diseases, neurological diseases, skin diseases, and other diseases were excluded from the research due to the relationship at $P > 0.05$. The results of entering all research variables by the Enter method are shown in Table 3.

Based on the results of Table 3, the variables including age ($P = 0.01$), heart diseases and arterial blood pressure ($P = 0.01$), diabetes mellitus ($P = 0.04$), the degree of dependence ($P = 0.01$), respiratory diseases ($P = 0.04$), cancer diseases ($P = 0.03$), mental disability ($P = 0.04$), physical performance ($P = 0.03$), ability to the emotional role ($P = 0.04$), positive state index ($P = 0.01$), negative state index ($P = 0.02$), formal social relationships ($P = 0.03$), and informal social relationships ($P = 0.01$) with $P < 0.05$ gained correlation statistically with QoL among the elderly. Other factors were excluded from the rest analysis with univariable analysis at $P > 0.05$. The results of entering the essential variables affecting QoL among the elderly from Pearson's Chi-square to Forward LR method in the last step of the model are shown in Table 4.

Based on the Forward LR logistic regression method, eight factors, including the degree of dependency ($P = 0.03$), diabetes mellitus ($P = 0.03$), formal social relationship ($P = 0.01$), informal social relationships ($P = 0.02$), ability to the emotional role ($P = 0.03$), physical performance ($P = 0.01$), heart

Table 2: Factors related to elderly's QoL by uni-variable analysis

Variable name	Variable type	Pearson Chi-square or Eta coefficient	*P*
Age	numerical	0.61	-
gender	binomial	12.1	0.15
marital status	polynomial	13.6	0.2
Education status	polynomial	12.3	0.21
place of residence	binomial	6.8	0.35
Heart diseases and arterial blood pressure	binomial	36.8	0.03*
Musculoskeletal diseases	binomial	18.16	0.02*
Diabetes Mellitus	binomial	17.7	0.03*
Digestive diseases	binomial	18.3	0.08
Respiratory diseases	binomial	11.6	0.03*
Neurological diseases	binomial	8.9	0.16
Cancer	binomial	11.7	0.04*
Mental disabilities	binomial	13.6	0.02*
Visual disabilities	binomial	15.2	0.01*
Hearing disabilities	binomial	11.7	0.01*
skin diseases	binomial	11.4	0.07
Other diseases	binomial	2.5	0.16
The degree of dependence	polynomial	33.3	0.01*
Physical performance	binomial	3.13	0.04*
physical pain	binomial	16.3	0.03*
Perceived health condition	polynomial	14.52	0.01*
The capability of emotional role	binomial	12.35	0.02*
Positive state index	polynomial	5.56	0.01*
Negative state index	polynomial	6.65	0.01*
Formal social relationships	polynomial	33.67	0.01*
general health	binomial	25.3	0.03*
Informal social relationships	polynomial	31.25	0.02*
hilarity	binomial	10.6	0.03*

Table 3: The results of the Enter logistic regression

Variable	Correlation	Odd ratio	Confidence interval	*P*
Age	0.25	0.665	0.45-0.86	0.01*
Heart diseases and arterial blood pressure	0.32	1.125	0.85-1.442	0.01*
Musculoskeletal diseases	0.21	0.43	0.221-0.662	0.11
Diabetes Mellitus	0.36	1.452	0.755-1.223	0.04*
respiratory diseases	0.27	0.977	0.853-1.165	0.04*
Cancer diseases	0.22	0.55	0.324-0.855	0.03*
Mental disability	0.31	0.64	0.421-0.0993	0.04*
Visual disability	0.26	0.334	0.228-0.471	0.09
Hearing disabilities	0.16	0.541	0.324-0.667	0.18
The degree of dependence	0.14	0.456	0.232-0.796	0.01*
Physical performance	0.26	0.335	0.192-0.441	0.03*
physical pain	0.12	0.171	0.085-0.193	0.09
Perceived health condition	0.31	0.846	0.554-1.067	0.1
The ability to emotional role	0.16	0.443	0.321-0.554	0.04*
Positive state index	0.17	0.995	0.835-1.379	0.01*
Negative state index	0.11	0.542	0.342-0.871	0.02*
Formal social relationships	0.35	0.842	0.835-1.379	0.03*
general health	0.13	0.325	0.245-0.531	0.12
Informal social relationships	0.36	0.778	0.535-0.831	0.01*
hilarity	0.14	0.227	0.835-1.379	0.17

Table 4: The factors affecting the elderly's QoL in the Forward LR of the BLR

Variable	Log-likelihood rate	-2 log-likelihood	Degree freedom (DF)	*P*
The degree of dependence	-36/666	8/215	1	0.03
Diabetes Mellitus	-37/083	9/049	1	0.03
Formal social relationships	-38/138	11/17	1	0.01
Informal social relationships	-85/233	105/349	1	0.02
The ability to emotional role	-54/881	44/646	1	0.03
Physical performance	-37/015	8/914	1	0.01
Heart diseases and arterial blood pressure	-54/975	44/834	1	0.02
Cancer	-38/221	11/326	1	0.01

diseases and arterial blood pressure ($P = 0.02$) and cancer diseases ($P = 0.01$) with $P < 0.05$ as significant factors were entered into the model at the final step. Also, the mean amount of Log-likelihood reduced to -47.776 from -253.35 without variables and only with a constant when these variables were entered into the model. This resulted in an increase in the model's efficiency at the final step. The results of comparing the performance of the two logistic regression models for QoL among the elderly using performance criteria, including sensitivity, specificity, accuracy, and F-measure in both train and test states, are shown in Figures 1 and 2, respectively.

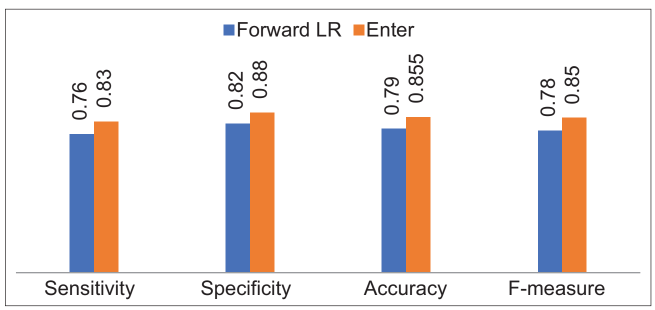

Figure 1: Comparing performance indicators of two selected regression models in train mode

According to Figure 1, the logistic regression model in the last step of the Forward LR with an accuracy of 0.79, a sensitivity of 0.76, a specificity of 0.82, and an F-measure of 0.78 compared to the Enter BLR with an accuracy of 0.855, a sensitivity of 0.83, specificity of 0.88 and F-Score of 0.85 had lower performance in training mode. Also, this method with accuracy an of 0.705, the sensitivity of 0.67, specificity of 0.74, and F-measure of 0.699, has lower performance than the Enter method, with an accuracy of 0.799, the sensitivity of 0.75, specificity of 0.84, and F-measure of 0.78 in test mode [Figure 2]. The results of comparing the performance of two models using the ROC curve are shown in Figure 3.

According to Figure 3, the logistic regression model with Enter method with an AUC of 0.82 in the training mode and 0.74 in the test mode have higher performance than the Forward LR method with an AUC of 0.755 in the training mode and 0.713 in the test.

Discussion

The current research aims to identify the most important factors affecting the QoL among the elderly using statistical methods. For this purpose, the relationship between each factor influencing QoL among the elderly was investigated using the simple correlation techniques including Chi-square test at $P < 0.05$ and Eta coefficient of more than 0.4. After identifying the important factors affecting the QoL among the elderly, they were simultaneously entered into two different methods of BLR, namely Forward LR and Enter, and the performance of two BLR models was investigated.

So far, various studies have been conducted concerning the role of ML and statistical methods in the physical, mental, and social aspects affecting the elderly's QoL. Byeon *et al*. developed a model for predicting physical disorders in older adults from three logistic regression, random forest, and XG-Boost algorithms. Their research showed that the XG-Boost, with an accuracy of 67%, a sensitivity of 81%, and a specificity of 75% using the SMOTE technique, had a higher performance than other ML algorithms. The variables of age, gender, educational status, insurance status, diabetes, arthritis, and stroke were identified as the most critical factors in predicting physical disorders in the elderly.[30] In the current study, diabetes mellitus, cancer, heart diseases, arterial blood pressure, and physical performance were considered critical physical factors affecting the elderly's QoL. Diabetes is one of the crucial factors that have an essential role in improving the QoL among the elderly mentioned in Byeon's study, similar to our study. Wong *et al*. investigated the elderly's QoL using environmental and geographical factors. In their study, the Forth European Quality of Life Survey (FEQLS) was used for this purpose. They used the Multivariate regression tree with cross-validation to assess the factors influencing QoL among the elderly. The results of their study showed that the most important factors are chronic physical and mental diseases, the ability to access health care services, the quality of health care services, income, security, education, social participation, and physical access to leisure places.[31] In the current study, chronic physical and mental disorders are detected as the most important factors predicting the elderly's QoL by binary logistic regression similar to Wong's study. In a study performed by Byeon *et al*., the social participation of the elderly was evaluated using two ML algorithms. The independent variable in this research was the social participation of the elderly in the last month, which had two values of yes and no. Variables describing the social participation of the elderly included demographic factors such as age, gender, education, occupation, physical abilities such as walking per week, and psychological factors such as stress and depression levels. Factors related to elderly participation were analyzed using an artificial neural network and QUEST algorithm. The results of the artificial neural network performance evaluation showed a mean squared error of 240.11 and the AUC was 0.718. Also, the accuracy of the training, testing, and validation data set was 75.8%, 72.8%, and 75%, respectively. The results of the performance evaluation of the QUEST decision tree showed an accuracy of 75.4%, which was obtained by 10 cross-validations.[32] In this study, social factors have a significant role in predicting the QoL among the elderly. Considering these factors to predict the QoL among the elderly caused the AUC of

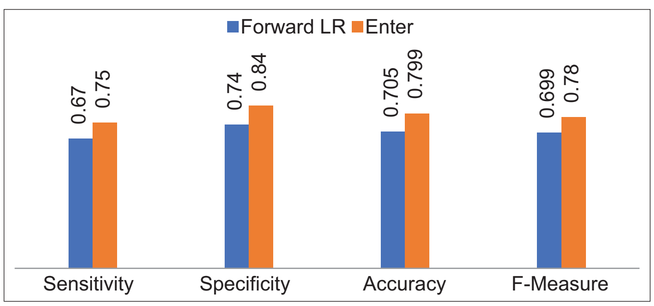

Figure 2: Comparing performance indicators of two selected regression models in test mode

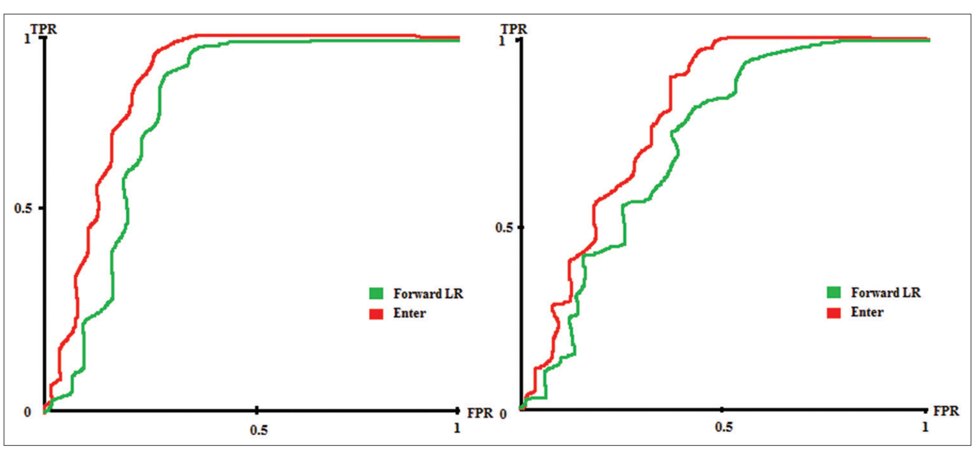

Figure 3: The ROC of two BLR states in training mode (left side) and testing mode (right side)

the Enter and Forward LR of BLR to reach 0.74 and 0.713, respectively. Asghari *et al*. used ML techniques to build a prediction system for Sucessfulaging (SA) and get the most important factors influencing the SA among the elderly. Their study showed that the prediction system with AUC = 0.96 with five-fold cross-validation could predict SA among the elderly. Also, life satisfaction and physical and mental factors are considered the important factors affecting SA among the elderly.[33] In this study similar to the Asghari *et al*. research, chronic physical and mental conditions are important in predicting the QoL among the elderly.

Na *et al*. investigated 35 factors in the elderly's QoL using an ML approach. These factors included nine main classifications of demographic, religious, and regional factors, indicators related to health and physical diseases, alcohol consumption, smoking, functional indicators, and well-being status to predict cognitive disorders in elderly communities. Their research showed that the age variable was the most influencing factor in this regard.[34] In the recent study, the age variable had a statistically significant relationship with the elderly's QoL using Pearson's Chi-square test. However, in the regression model, they did not have meaningful correlation power. Lee *et al*. have tried to identify the most critical predictors of favorable and unfavorable QoL among the elderly based on ML methods. Multivariate regression was used to determine the importance of determinant factors for predicting the QoL among the elderly. The results showed that the hand-shaking power, with a beta correlation of 1.71 for men and 1.74 for women, was the essential factor associated with physical indicators. Hand-shaking power variables, walking speed, and chronic diseases were considered the most important biological factors related to mental markers predicting the QoL among the elderly.[35] Paying attention to physical factors is among the most essential and influential variables in improving the elderly's QoL, which also had a high correlation in the present study.

Strength and limitation

The strength of this study was using various factors including physical, mental, and social factors influencing the elderly's QoL, and considered more social factors in contrast with previous studies. Among the limitations of the research was that due to comprehensiveness and considering all dimensions in predicting the quality of life of the elderly, some critical factors may not be available in the database and, therefore, not analyzed. In addition, three elderly centers were used to extract data and identify important factors for predicting the elderly's QoL, which may have limited the model's generalizability. Some variables, such as the total scores in the dependency index, were quantitative. Still, they were stored qualitatively in the database, which may have affected the model's performance to some extent. For future studies, we suggest more samples in various elderly centers and more social factors in the dataset for increasing the generalizability and betterment of the prediction model in addition to increasing the prediction model performance. Although the elderly's QoL is a qualitative approach, we recommend as much as possible using quantitative factors for increasing the model precision. The mentioned methods for training the statistical model will discover the predictor factors influencing the elderly's QoL. This causes us to find the best factors with more generalizability to modify and therefore increase life satisfaction and QoL among the elderly. The elderly with this approach have a higher QoL with less physical, mental, and more important of them higher social participation at the societal level.

Conclusion

Identifying the effective factors for the elderly's QoL and attempting to modify them through the physical, mental, and social aspects have a significant role in enhancing the elderly's clinical and health outcomes. The rate of physical and mental disorders in the elderly's will be decreased, and social participation will be increased in this way, so this will prevent low QoL among the elderly in an effective way. Also, the clinical cost of this aged-group people will be decreased at the societal level and physicians can get more informed and effective clinical decisions for the elderly. The resource will be assigned to preventive health measurements rather than expensive clinical costs by health managers and policymakers. Therefore, changing policies in allocating resources in this way will save the cost of health at the macro level in society. This strengthens policymaking in the health sector by investing in new strategies by health managers and policymakers to increase the health and well-being of the elderly.

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Nil.

Conflicts of interest

There are no conflicts of interest.

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