Original Article

Establishment of Age-predictive Equation for Japanese Women Based on Simple Physical Fitness Measurements and Blood Pressure

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Abstract

The purpose of this study was to discuss the procedures for establishing indices for physical senility from simple physical fitness tests through linear regression analysis. The fluctuation of residuals obtained from the various regression analyses and the statistical procedures for dealing with the variables when the assumptions concerning the residuals were contradicted, were discussed. In this study, 168 females (mean age 37.7, SD 11.3, range 20 to 65 years) who were registered with one occupational insurance organization were examined. They each underwent tests to establish readings for seven variables, including five physical fitness tests: standing trunk flexion (FLEX), sit-ups in 30 seconds (SIT-UP), vertical jump (VERT), repetitious side step in 20 seconds (SIDE), and step test (STEP-ME). Two blood pressure readings while at rest were also taken (SBP, DBP). The results can be summarized as follows. In the forward stepwise regression analysis, the order of entered variables was VERT ($R=0.637$), SIT-UP ($R=0.673$), DBP ($R=0.696$), FLEX ($R=0.704$), and SIDE ($R=0.717$). The equation is $\hat{y}=61.38-0.569 \times (\text{VERT})-0.513 \times (\text{SITUP})+0.183 \times (\text{DBP})+0.283 \times (\text{FLEX})-0.328 \times (\text{SIDE})$. Minimum AIC estimates (MAICE) were achieved for this equation. The correlation coefficient between residuals and predicted value was 0.345 ($p<0.05$). To satisfy the assumptions of the standard regression model, the researchers worked with transformed variables instead of working with original variables. The transformations of the raw data into logarithms and into reciprocals is described. According to the rules of variable elimination using ridge regression analysis, SBP and STEP-ME were eliminated from the set of seven variables. However, an examination of the residuals indicated that there were no advantages with

using these transformations compared to the general linear model using raw data. The ratio of the predicted age for each client obtained from the predictive equation and chronological age is regarded as a marker of aging. Therefore, it is necessary for researchers to examine what kind of life styles result in such individual differences.

Key words : age prediction, regression analysis, physical fitness test, Japanese women

Introduction

With a long-life society rapidly developing into one with long life expectancies, all people are hoping to grow old while maintaining their health. In addition, healthy aging, which means growing old while retaining one's vitality, is essential remove spaces like this throughout document to the development of society.

Gerontology is the investigation of the subject of aging and the attempt to delay the symptoms of aging¹⁾. However, the phenomena of aging cannot be briefly discussed in terms of causality. Therefore the phenomenon are intangible as an object of science, and there is little prospect of establishing a conceptional definition of aging. Furthermore, some have suggested that the essential nature of aging may be lost if diverse opinions are unified too hastily and by force²⁾.

In this study, the term senility is roughly defined as a decrease in physical fitness functions consequent to aging; senility in its narrowest sense will indicate pathological senility with an undesirable decrease in activity that is observable and the result of aging. In other words, the term *physical senility* will be used to describe a condition where the degree of deterioration or aging is greater than that seen by a normal aging curve.

It is necessary to establish a generalized aging curve of human beings in order to describe the extent of an individual's senility. Procedures for establishing biological senility indexes that are biomarkers of aging,

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and which have both high validity and reliability have been developed in various fields such as anthropology, the medical sciences, and biochemistry³⁻⁶⁾. The authors^{7,8)} developed a method to estimate the way, the chronological age of a person using factors such as his/her movement and physiological or morphological variables such as teeth attrition. This method employs the statistical technique of linear regression analysis.

In this analysis, the procedure for estimating the regression coefficient is based upon factors closely related to age such as movement, physiological and morphological variables, and actual chronological age. A person for whom the index of estimated age/chronological age is more than 100% can be considered physiologically older than he/she actually is. On the other hand, if this index is less than 100, he/she can be considered physiologically younger. In order to build up a predictive model to evaluate an individual's physical fitness senility, the following conditions are necessary: (1) The independent variables must accurately reflect biological aging. (2) The independent variables must be easily measured. (3) The contents of the measurements must be understandable by both the subjects and the tester. When tests satisfying these conditions are given to subjects, those who are evaluated as older than their chronological age should be able to change their behavior so as to increase their physical fitness level.

In regression analysis, the following elements must be considered: the accuracy of the regression model: the selection of an appropriate model, the estimation of the parameters, the evaluation and confirmation of model validity, and the interpretation of the results. Diagnostic elements must also be considered, but the most important element is the examination of residuals. A detailed examination of the residual plots will reveal important information concerning any inconsistencies in regression assumptions⁹⁻¹²⁾. Residual systems can be considered estimates of the system of error terms. Therefore, residual systems are an important information source through which the possibility of any inconsistencies in residuals can be examined.

Neither physical fitness research nor medical research has established a general aging model for predicting with chronological age using synthetic fitness tests with the independent variable of residency in rural or urban region. The purpose of this study was to establish for evaluating by linear regression analysis for physical senility using simple physical fitness tests. A second aim of this study was to examine the fluctuation of the residuals obtained from the various regression analyses, and the statistical procedures for dealing with the variables when the assumptions concerning the residuals are contradicted.

Materials and Method

1) Subjects and Data Collection

In this study, 168 females (mean age 37.7, SD 11.3, range 20 to 65 years) who were registered with one occupational insurance organization were examined. Each underwent tests to establish readings for seven variables, including five physical fitness tests: standing trunk flexion (FLEX), sit-ups in 30 seconds (SIT-UP), vertical jump (VERT), repetitious side step in 20 seconds (SIDE), and step test established by the Ministry of Education, Science, Sports, and Culture Ministry (STEP-ME). (Tokyo Metropolitan University, 1989)¹³⁾. Two blood pressure readings while at rest were also taken (SBP, DBP). A medical doctor or public health nurse took the measurements of blood pressure while resting with a mercurial sphygmomanometer.

2) Selection of Variables in Regression Analysis

After computing the descriptive statistics and correlation coefficients between variables, forward stepwise regression analysis was applied to establish the optimal equation, adopting F-to-enter to stop the entry of variables.

(1) Procedures for selection of optimal equation

In the stepwise linear regression analysis, the equation was designed in the following manner¹⁴⁻¹⁶⁾. The analysis of the variance table for regression analysis included the following statistics: regression sum of squares = sum of squares of residuals between the estimated value and the average; residual sum of squares = sum of squares of the observed value and the estimated value; F-ratio = regression mean square divided by the residual mean square.

The F-ratio is an overall test of the significance of the coefficients of the independent variables in the regression equation. Generally, the selection of variables for inclusion in the equation is made to maximize the F-ratio. In other words, the level of significance of the F-ratio cannot be obtained from the standard F distribution, so it is unclear what probability is associated with each F statistic.

F-to-remove tests the regression coefficient to determine the relative importance of variables already in the equation. It is equal to the ratio $\{SS(\text{removed}) - SS(\text{residuals})\} / SS(\text{residuals}) / (N - p')$ where $SS(\text{removed})$ is the sum of squares of residuals after removing the independent variable in question. If the F-to-remove of a variable is less than the acceptable limit and less than the value for the other variables entered, the variable is removed from the equation. The F-to-remove values are helpful in determining the relative importance of the selected variable at a given step.

F-to-enter tests the regression coefficient for each of

the remaining independent variables as if these were entered separately into the equation at the next step. Let SS (residuals) be the sum of squares of residuals at this step and SS (next) be the residual sum of squares after the potential independent variables entered. Then F-to-enter is the ratio $\{SS(\text{residuals}) - SS(\text{next})\} / \{SS(\text{next}) / (N - p' - 1)\}^{14}$.

The F-to-enter value indicates the degree to which the independent variable would enhance the prediction of the dependent variable by entering the equation next. The usual table of F values (percentiles of the F distribution) should not be used to test the need to include a variable in the model because the distribution of the largest F-to-enter is affected by the number of variables available for selection, their correlation structure, and the sample size. When the independent variables are correlated, the critical value for the largest F can be much larger than the value when testing one pre-selected variable. Consequently, using the usual table of F values can yield a predictive equation with so many variables that the equation performs poorly on new data.

The analysis of residual (e_i), which is the difference between predicted value and actual value, was assumed to be independent, have a zero mean, have a constant variance σ^2 , and follow normal distribution.

(2) Statistical Criteria for Evaluating the Equation

The following independent information criteria were used to select the best model of all possible subsets: the minimum AIC (Akaike's Information Criterion)^{17,18}, the minimum absolute difference between Cp statistics and p^{19} , the number of regressors or independent variables in the reduced model, and the SIC statistics, which are a correction of the Bayesian-based AIC statistics²⁰.

Collinearity is assessed for the reduced models using the condition number (CN) computed for the standardized residuals with the intercept included. Although no specific cut-off has been established, Besley *et al.* suggest that a CN of 30 indicates probable collinearity in the model¹⁴.

(3) Detection of Multicollinearity

A ridge regression analysis deflates correlation values, reducing the effects of multiple collinearity; using such a regression analysis, the influences of each independent variable on the dependent variable can be more clearly seen.

One of the goals of ridge regression is to create a regression equation with stable coefficients. The coefficients are stable in the sense that they are not affected by slight variations in the estimation data. The objectives of a good variable selection procedure are (1) to select a set of variables that provides a clear understanding of the process under study and (2) to formulate an equation that provides accurate forecasts of the response variable in terms of values that can be

applied to other explanatory variables beyond those which are being studied at any one time. It should be noted that the objectives of a good variable selection procedure and ridge regression are very similar, and consequently, ridge regression can be employed to accomplish variable selection⁹.

Examining the ridge trace, a plot of the ridge regression coefficients against the ridge parameter k , does the variable selection. For a collinear system, the characteristic pattern of the ridge trace has been previously described in the literature^{9,12}. The ridge trace is used to eliminate variables from the equation. The rules for elimination are described by Hoerl and Kennard²¹ as follows.

1. Eliminate variables whose coefficients are stable but small. Since ridge regression is applied to standardized data, the magnitude of the various coefficients is directly comparable.
2. Eliminate variables with unstable coefficients that do not retain their predictive power, that is, unstable coefficients that tend to reach zero.
3. Eliminate one or more variables with unstable coefficients. The variables remaining form the original set, for example p in number, are used to for the regression equation.

(4) Examination of Residuals

The plotting of residuals and their predicted value is useful in detecting such problems as a lack of linearity, a lack of constant variance, outliers, gross errors, and an unusual subpopulation that should be separated from the analysis. The plotting may also indicate that transformations of the data are advisable or that an inappropriate model has been chosen. In addition, it is necessary to examine problems that arise in setting up the predictive equation, such as multicollinearity^{9-12,22}.

Results

1) Selection of Variables in Regression Analysis

Table 1 shows descriptive statistics and includes the correlation coefficients among age and the seven independent variables.

The F-to-enter value indicates the degree to which the independent variable would enhance the prediction of the dependent variable by entering the equation next (Table 2).

2) Statistical Criteria for Evaluating Equation

Table 2 describes the residual sum of squares, squared multiple correlation coefficients (R), adjusted R for the degree of freedom (R^*), and three information criteria for variable selection (AIC, Cp, SIC). VERT is the first variable entered into the equation, followed by SIT-UP in the 2nd step, DBP in the 3rd step, FLEX in the 4th step, SIDE in the 5th step, STEP-ME in the 6th step, and lastly SBP.

In forward stepwise regression analysis, the variable

Table 1 Descriptive statistics and correlation coefficients among independent variables and age.

	MEAN	SD	AGE							
AGE	37.67 y.o	11.300	1							
FLEX	12.2 cm	5.890	-0.118	1						
SITUP	14.3 times	5.260	-0.554	0.306	1					
VERT	35.5 cm	7.340	-0.637	0.320	0.597	1				
SIDE	37.4 times	6.590	-0.552	0.404	0.576	0.671	1			
STEP	53.5	20.200	-0.113	0.024	0.117	0.062	0.104	1		
SBP	109.9 mmHg	13.300	0.229	0.008	-0.071	-0.213	-0.074	0.179	1	
DBP	69.2 mmHg	10.200	0.342	0.021	-0.171	-0.252	-0.203	0.003	0.671	1

VERT : vertical jump, SITUP : sit ups in 30 sec., FLEX=trunk flexion, SIDE : side step test in 20 sec., STEP : modified step test in 30 sec., SBP : systolic blood pressure, DBP=diastolic blood pressure.

Table 2 Order of entered variables and statistics of criteria forward stepwise regression analysis at each step.

step No.	Entered variable	sqr. R×1000	AIC/100	Cp	SIC/100
1st.	VERT	405	15.718	28.86	15.6730
2st.	SITUP	452	15.601	16.65	15.5460
3rd.	DBP	485	15.512	7.99	15.4520
4th.	FLEX	496	15.503	6.50	15.4270
5th.	SIDE	514	15.464	2.90	15.3788
6th.	STEP	518	15.475	4.02	15.3794
7th.	SBP	520	15.485	5.09	15.3796

sqr. R : Squared multiple correlation coefficient, AIC : Akaike's Information criterion, CP : Malows criterion, VERT : vertical jump, SITUP : sit ups in 30 sec., FLEX : trunk flexion, SIDE : side step test in 20 sec., STEP : modified step test in 30 sec., SBP : systolic blood pressure, DBP : diastolic blood pressure.

whose addition would increase R^2 , that is the variable with the largest F-to-enter, is entered at each step. Consequently, R^2 increases as the number of independent variables entered into the equation increase. In the forward stepwise regression analysis, the order of entered variables was VERT ($R=0.637$), SITUP ($R=0.673$), DBP ($R=0.696$), FLEX ($R=0.704$), SIDE ($R=0.717$). The other variables were statistically insignificant. The equation was $\hat{y}=61.38-0.569 \times (\text{VERT})-0.513 \times (\text{SITUP})+0.183 \times (\text{DBP})+0.283 \times (\text{FLEX})-0.328 \times (\text{SIDE})$. The obtained equation, described by β (standardized regression coefficients) was $\hat{y}_b=-0.370 \times (\text{VERT})-0.239 \times (\text{SITUP})+0.165 \times (\text{DBP})+0.148 \times (\text{FLEX})-0.192 \times (\text{SIDE})$.

3) Improvement of Predictive Equation After Data-transformation

Table 2 and Figure 1 show the changes in the values of the information criteria AIC, Cp, and SIC as well as the entered variable at each step using forward regression analysis. VERT, which had the largest F-to-enter value, was the variable entered in the first step. In the following steps, the other variables were entered into the equation in the order SIT-UP, DBP, SIDE, FLEX, STEP-ME, and SBP, in accordance with their F-to-enter values. However, minimum AIC estimates (MAICE) were achieved when the equation included

Figure 1 Changes in criteria each step.

sqr. R : Squared multiple correlation coefficient, AIC : Akaike's Information criterion, CP : Malows criterion, VERT : vertical jump, SITUP : sit ups in 30 sec., FLEX : trunk flexion, SIDE : side step test in 20 sec., STEP : modified step test in 30 sec., SBP : systolic blood pressure, DBP : diastolic blood pressure.

five variables but without the two variables STEP-ME and SBP (Figure 1). In other words, these two variables did not contribute to the predicted value for

Table 3 Ridge regression coefficients at k=0 to 1.0

k	FLEX	SITUP	VERT	SIDE	STEP	SBP	DBP	sqr. R
0.0	0.144	-0.235	-0.371	-0.188	-0.010	0.005	0.164	0.515
0.1	0.116	-0.227	-0.332	-0.191	-0.043	0.025	0.146	0.513
0.2	0.096	-0.218	-0.305	-0.188	-0.044	0.036	0.136	0.509
0.3	0.080	-0.210	-0.284	-0.184	-0.040	0.043	0.128	0.503
0.4	0.067	-0.202	-0.267	-0.180	-0.043	0.047	0.122	0.497
0.5	0.057	-0.195	-0.253	-0.175	-0.042	0.049	0.117	0.4908
0.6	0.048	-0.188	-0.240	-0.170	-0.041	0.050	0.112	0.484
0.7	0.041	-0.181	-0.230	-0.162	-0.040	0.051	0.109	0.4786
0.8	0.035	-0.175	-0.220	-0.161	-0.039	0.051	0.108	0.47
0.9	0.030	-0.169	-0.211	-0.156	-0.038	0.051	0.102	0.463
1.0	0.026	-0.164	-0.203	-0.152	-0.037	0.051	0.098	0.4565

sqr. R : Squared multiple correlation coefficient, VERT : vertical jump, SITUP : sit ups in 30 sec., FLEX : trunk flexion, SIDE : side step test in 20 sec., STEP : modified step test in 30 sec., SBP : systolic blood pressure, DBP : diastolic blood pressure.

chronological age.

The assumptions on the fluctuation of residuals for an individual were evaluated by plotting the residual and predicted value. Figure 2a shows the relationship between the predicted age and standardized residuals (e_{is}). Standardized residuals was defined as the ratio of individual residuals to the SD of residuals. Plotting was randomly fluctuated around a value of zero for e_{is}. When the descriptive statistics of the residuals obtained from the equation based on the raw data were calculated, the skewness and kurtosis were -0.169 and -0.039, respectively. The correlation coefficient between residuals and predicted value was 0.345 ($p < 0.05$). By the plotting the residuals and computing the descriptive statistics, there was no problem with this general linear model.

4) Ridge Regression Analysis to Detect Multi-Collinearity

Table 3 shows the standardized ridge regression coefficients at $k=0.1$ to 1.0. According to the rules of variable elimination described above, SBP and STEP-ME were eliminated from the set of seven variables. Therefore, a set of five variables was used to form an equation with stable coefficients, and as Table 3 demonstrates, the ridge trace is stable at $k=0.3$. The equation with the best fit in terms of standardized variables is $\hat{y} = 0.079 \times \text{FLEX} - 0.210 \times \text{SITUP} - 0.284 \times \text{VERT} - 0.184 \times \text{SIDE} + 0.128 \times \text{DBP}$.

Discussion

The subjects in this research are associated with the occupational insurance organization and its employees, and although they are working in agriculture. However, they are all people who live healthy daily lives. Therefore, the age estimating model developed using these subjects is also effective as a general model. Consequently, this model can be used to

predict the age of the individuals and to account for differences in the physical senility of each occupational category for the presumed physical fitness age.

Among people of the same chronological age, some individuals have higher scores than the standard aging score while some individuals have lower scores than the standard aging scores. The authors have taken notice of these individual differences, as discussed above.

1) Detection of the Optimal Predictive Equation

In many applications of regression analysis, the set of variables to be included in the regression model is not predetermined, and the first part of the analysis is often the selection of these variables. Before discussing actual selection procedures, some preliminary remarks should be made. It is not usually meaningful to speak of the best set of variables to be included in the multiple regression equation. There is no unique best set of variables. A regression equation can be used for several purposes. The set of variables that may be best for one purpose may not be best for another. The purpose for which a regression equation is constructed should be considered during the variable selection process because the purpose determines the criteria for selecting and evaluating the contributions of different variables⁹⁾.

First, in order to achieve an optimal regression model, several information criteria for variable selection, such as AIC and Mallows Cp, were applied. Second, in order to examine the deficiency of the general regression model, we examined the residuals from obtained models using visual observation and descriptive statistics. Akaike¹⁷⁾ suggested that achievement of MAICE (minimum AIC estimate) in regression analysis was equal to the variable selection in forward stepwise regression analysis in which the F limit value was set at 2.00. In this study, the F-limit

was set at 2.0 and the variables selected as significant in stepwise regression analysis were the same as using ridge regression analysis.

2) Examination of Residual Analysis and Improvement of Regression Analysis

When residuals were plotted on the y-axis and predicted values on the x-axis (Figure 2a), the variance of residuals was small when predicted age was small but had gradually grown as predicted age grew. Consequently, from residual analysis of this general model, we obtained a called trumpet-shaped distribution.

In this study, different regression analyses including serial analyses of the general linear regression model, transforming the data into logarithms or into reciprocals, and ridge regression analysis were used to determine the most optimal age-predictive model. If a specific relationship between the residuals and predicted values is observed, the transformation of an independent/dependent variable into other numerical values is feasible^{10,12)}. Transforming the raw data into logarithms, or reciprocals was considered necessary to establish the appropriate indices for physical senility using the sports-oriented physical fitness variables used in this study.

The equation to transform the independent variables into logarithms was $\hat{y}_{\log} = 104.1 - 21.2 \times \{\log(\text{VERT})\} - 10.9 \times \{\log(\text{SIDE})\} - 5.64 \times \{\log(\text{SITUP})\} + 13.29 \times \{\log(\text{DBP})\} - 2.72 \times \{\log(\text{FLEX})\}$, and the multiple correlation coefficient was 0.7091 ($R^2 = 0.5027$). In this logarithmic transformation of the independent variables, seven subjects were deleted from the data analysis since their measurements of trunk flexion (FLEX) were below

zero.

The equation to transform the independent variables into reciprocals was $\hat{y}_{\text{rec}} = 17.48 + 792.9 \times (1/\text{VERT}) + 319.8 \times (1/\text{SIDE}) + 18.99 \times (1/\text{SITUP}) - 907.2 \times (1/\text{DBP}) - 2.26 \times (1/\text{FLEX})$, and the multiple correlation coefficient was 0.7091 ($R^2 = 0.463$). In this reciprocal transformation of independent variables, the measurements of trunk flexion (FLEX) for five subjects had negative values.

Figure 2b shows the relationship between the predicted age and standardized residuals (e_{is}), the latter being defined as the ratio of individual residuals to the SD of residuals obtained from log transformations. Plotting with predicted ages resulted in a trumpet-shaped distribution, which is similar to the general model. The systematic patterns of the distribution of the residuals after using the equation for reciprocal transformed data is not satisfactory, and neither are the patterns from the equation on the equation on logarithmic transformed data.

Consequently, there is marked evidence of the constancies of error variance in these transformed models. Because, the distribution of residuals shows a certain distinct pattern, it must be concluded that the transformed models are inadequate. Examining the various information criteria, the optimal model appears to be the general linear regression equation using four fitness measurements and diastolic blood pressure. However, as a result of an examination of residuals, it is obvious that the advantages of models with data transformed into logarithms and reciprocals were not superior to the raw data in the general model.

The analysis and confirmation of residuals is essential to the adequacy of regressive models.

Figure 2a Scattergram of predicted age and standardized residuals.

Figure 2b Scattergram of predicted age and standardized residuals after log-transformed.

Checking regression models includes residual examination, and the importance of plotting and examining residuals cannot be overemphasized. Residual examination should be as much a part of a regression analysis as the estimation of the regression coefficients themselves²³⁾. However, this examination of residuals has often been overlooked in predicting age, particularly, in the medical and paramedical sciences. In the future, more consideration should be given to developing the most appropriate predictive model for selecting variables and analyzing residuals using the procedures that have been outlined above. Furthermore, in the reciprocal or logarithmic transformation of independent variables, some subjects were deleted from the data analysis since their measurements, such as those for trunk flexion (FLEX), were below zero. Therefore, there was no advantage to using these transformations when compared to the general linear model using raw data.

There are several problems that are unavoidable when developing the optimal predictive model for the markers of aging in this discipline. The present paper was characterized by two statistical approaches. In developing an optimal predictive equation for physical fitness age, we will inevitably confront various unavoidable problems, including the following: (1) the existence of multicollinearity due to the high correlations among independent variables and (2) the decline in confidence of estimation due to a reduction in the degrees of freedom with many independent variables and a small number of observations. As for the solution to the first problem, the ridge regression equation or the principal component regression analysis is possible. The objectives in the selection of variables using both stepwise regression analysis and

ridge regression analysis are very similar. Using ridge regression analysis, the avoidance of the effect on multicollinearity has been recognized. However, some statistical criticisms have been made. Asano²⁶⁾ questioned whether ridge regression improves the degree of interpretation about the parameter.

In this study, the selected variables were the same for the general regression model and the ridge regression analysis. Furthermore, other statisticians have criticized ridge regression analysis from the viewpoint that the prior information for distribution should be considered at the beginning of the data analysis²⁴⁾.

In consideration of these arguments, it is not necessary to use the ridge regression analysis instead of a general linear model. Therefore, these regressive multivariate analyses may be used to develop the optimal equation for age prediction. In conclusion, the authors would like to propose the general linear model using raw data as the most optimal and valid model.

3) Cross-validation of Predictive Equation

In order to assess the stability of the general linear model developed in the present study, predicted age was computed using the average score of the measurements with the data from Tokyo Metropolitan University¹³⁾ for those 30 through 55 years of age. As a result, the correlation coefficient of the chronological age and the predicted age from this general model was 0.9996, and the t-value of the differences between the two ages of each subject was 4.08 ($p < 0.001$). Although there was an overestimation of chronological age, the cross validation of the general linear model was verified on the whole.

4) Availability of Predictive Equation

In this study, since the squared multiple correlation

coefficients in both equations are greater than 0.5, the established models do not display sufficient validity. This indicates that other variables should be added as independent variables. Considering other possible variables, in the aging research by Furukawa *et al.*³⁾ a linear regression model was developed that utilized the following variables: heart rate after exercise, body height, body weight, SBP, vital capacity, PSP, vibration in finger, eye accommodation, serum cholesterol, hemoglobin, total protein, icterus index, RBC, WBC, GFR, and RPF. However, the adequacy of the model is influenced by the degrees of freedom (=the differences in the number of observations and parameters). Reducing the degrees of freedom results in a decline in confidence in the estimation. In other words, a person for whom the index of estimated age/chronological age is more than 100% can be considered physiologically older than he/she actually is. On the other hand, if this index is less than 100, he/she can be considered physiologically younger. In regression analysis, VERT and SIDE, reflecting the agility and power elements of physical fitness, were selected as the first or second variables. Consequently, VERT is the most important factor reflecting the aging process of human beings.

Recent muscular physiological research has clarified the effect of aging on skeletal muscles. Aging results in a gradual loss of muscle function, and there are predictable age-related alterations in skeletal muscle function. At the cellular level, muscles lose both cross-sectional area and fiber numbers, with type 2 muscle fibers being the most affected by aging. Aged skeletal muscle produces less force, and there is a general slowing of the mechanical characteristics of the muscle²⁶⁾. The ageing atrophy that begins around 25 years of age and thereafter accelerates is caused mainly by a loss of muscle fibers and to a lesser extent by a reduction in fiber size, mostly in proportion to the fiber area in the muscle cross-section occupied by type II fibers^{25,26)}.

In general, the health-oriented physical fitness test has been recognized as a more optimal one than the sports-oriented fitness test. However, in order to clarify the age decline of physical function, certain measurements of the sports-oriented fitness test such as agility and muscular power have been recognized as useful. In order to establish an age-predictive equation with high validity, tests to evaluate agility and the speed of muscular contraction should be established. Consequently, the "Sports Test of the Ministry of Education and Science" should often be used in aging research.

Furthermore, goodness of fit in the obtained equations obtained in this study should be increased and is, therefore, an additional problem. In developing an age-predictive model with excellent goodness of fit,

we should create a set of independent variables closely related to the aging process. The classification of the living body's cells into four groups was proposed by Cowdry²⁷⁾. They are: (1) the vegetative intermitotics such as the stem cells in skin, (2) the differentiating intermitotics such as the stem cells of the spinal cord and red blood cells, (3) the reverting post mitotics such as the cells of smooth muscle or liver cells, and (4) the fixed post mitotics such as neurons or cells of the cardiac muscle.

One problem in the aging research with human beings is whether the proliferative ability of the vegetative intermitotics decreases with aging and whether the fixed post mitotics are available with aging. In this study, subjects were evaluated for cardiac functions by measuring changes in heart rate after a step test of three minutes (STEP-ME) and by taking the blood pressure twice (SBP, DBP). In addition, the vertical jump (VERT) and side-step test (SIDE) were used as measures of the muscle strength of the lower limbs and the agility of the whole body. Trunk-extension (EXT), although not a variable in the present study, can be used to measure physical. It was found that these tests to measure physical fitness are a proper index that reflects the state of the aging of motor neurons. Collectively, these tests collectively are the physical fitness test battery established by the Japanese Ministry of Education in 1964. This test battery does not require much expense and is easy to administer.

Based on the results discussed above, the predictive model presented in this study can measure the physical fitness related to senility in such a way that it is realistic, understandable, and is easily measured. These elements are very important in allowing one to create concrete health prescriptions such as those concerning exercise and diet.

As a final comment, the idea can be advanced that researchers of aging adopt the fixed post mitotic cells as physical fitness markers of aging. Accordingly, variables such as the following should be set up as the independent variables: blood pressure while at submaximal exercise, dental attrition, and sensory motor skills such as eye-hand and eye-leg coordination.

Some researchers have recently applied both factor analysis and multiple regression analysis to the derivation of physical functional status^{6,28)}. The advantage of adopting this procedure is being able to avoid the overestimation of functional age for a younger person and underestimation for an older person²⁹⁾. However, the understandability of the markers of aging for clients and the ease of measurability for testers or for researchers are also of great importance since they will determine the behavioral feasibility of implementing a program

designed to delay premature aging. Therefore, a linear model for age-prediction was established. The goodness of fit of this model, as evaluated through the multiple correlation coefficient, was not satisfactory.

In this study, statistical problems in establishing an age-predictive model for women, such as adopting information criteria and examining the residual of the regression model obtained from the raw data and the extracted transformed data, were discussed. These statistical problems can be applied in establishing the age-predictive models for the other gender.

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