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Neural network and multiple linear regression to predict school children dimensions for ergonomic school furniture design

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A R T I C L E I N F O

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A B S T R A C T

The current study investigates the possibility of obtaining the anthropometric dimensions, critical to school furniture design, without measuring all of them. The study first selects some anthropometric dimensions that are easy to measure. Two methods are then used to check if these easy-to-measure dimensions can predict the dimensions critical to the furniture design. These methods are multiple linear regression and neural networks. Each dimension that is deemed necessary to ergonomically design school furniture is expressed as a function of some other measured anthropometric dimensions. Results show that out of the five dimensions needed for chair design, four can be related to other dimensions that can be measured while children are standing. Therefore, the method suggested here would definitely save time and effort and avoid the difficulty of dealing with students while measuring these dimensions. In general, it was found that neural networks perform better than multiple linear regression in the current study.

1. Introduction

Primary school students spend much of their time sitting on chairs daily. Bad design of furniture may lead to health and learning problems. Therefore, design of furniture with proper dimensions is critical to encourage appropriate postures (Straker et al., 2010). So many studies were conducted to ergonomically design the school furniture using anthropometric measurements which vary according to many factors. Most of these studies showed school children frequently use furniture that is not suited to their anthropometry (Straker et al., 2010). Anthropometric measurements are not easy to perform and they need a large sample size and a lot of dimensions. Some of these dimensions are necessary to ergonomically design the chair and yet they are not easy to measure. This study attempts to find some easy-to-measure dimensions that are capable of predicting the difficult-to-measure ones used in designing school furniture for primary school students.

2. Literature review

Although measuring all the necessary body dimensions is very expensive and time consuming, little was published on how to predict difficult-to-measure dimensions from easy-to-measure ones. It is necessary to know the interrelationships between dimensions to predict additional ones (Haslegrave, 1980). The existing studies can be classified into studies that used a single variable (predictor) and others that used multiple variables. Jeong and Park (1990) used stature alone to predict the dimensions needed to design school furniture. The results show that different regression equations are needed for males and females. Another study by Lewin (1969) studied the relationship between some anthropometric measures and found that some differences exist in the regression equation between males and females. It is noted that the study still used a single variable. Al haboubi (1992) also used a single variable regression model to obtain some anthropometric dimensions using weight and stature for Easterners population. Chao and Wang (2010) used Constant Body Ratio (CBR) benchmarks to convert old anthropometric data into new data. In other words, these CBRs are used to predict new data from old data. 197 estimation formulae using 19 easily measured dimensions were built using a total of 483 CBR benchmarks. Ma et al. (2011) studied the body characteristics of adult Koreans aging between 18 and 59 using a three-dimensional scan. The body of each adult was divided into 16 segments and the mass inertial parameters were estimated by assuming that the density of each segment is uniform. At least one circumference of each segment and the length were determined for scanned data. Body segment parameters were then estimated using nonlinear regression equations as a function of length and circumference. A study by Kaya et al. (2003) used

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adaptive neuro-fuzzy inference system to estimate anthropometric measurements. However, the study used 18 body dimensions to predict six dimensions. To measure all these 18 dimensions is still not an easy task. This study uses only four anthropometric dimensions to predict five essential ones needed for ergonomic design of primary school furniture using multiple linear regression and neural networks.

2.1. Ergonomic furniture design

Workplace furniture design and user anthropometry have become an important consideration in designing ergonomically appropriate furniture (Van Wely, 1970; Harris et al., 2005). School children are at risk of suffering negative effects from ill-fitting furniture (Parcells et al., 1999). The use of proper furniture design reduces fatigue and discomfort in the sitting posture. According to Cranz (2000), correct standing and sitting postures would help in the prevention of musculoskeletal symptoms. The anthropometric dimensions needed to determine school furniture dimensions that promote a correct sitting posture include popliteal height, knee height, buttock popliteal length and elbow height (Knight and Noyes, 1999; Parcells et al., 1999; Panagiotopoulou et al., 2004; Gouvali and Boudolos, 2006; Chung and Wong, 2007; Agha, 2010; Straker et al., 2010).

2.2. Predictive models

A large number of different predictive models have been proposed over the years. Despite the number of research activities, there is still a doubt to advise practitioners as to what prediction models they should select, because studies have not converged to similar answers. There are a number of factors that should be considered in the selection of a prediction technique, and it is likely that trade-offs will need to be made in the process. Technique selection is driven by both organizational needs and capability. In terms of need, the most common aim is to maximize the accuracy in prediction; however, other issues may also need to be considered. For instance, a technique that produces slightly less accurate but generally more robust models might be preferred, especially in cases where the organizations do not have access to locally calibrated, well-behaved data sets. While it is very positive that more sophisticated (and potentially more useful) techniques are being employed to build predictive models, genuine benefits will be achieved if the techniques are appropriately used (Tronto et al., 2007).

2.2.1. Multiple linear regression

Many problems in engineering and science involve exploring the relationships between two or more variables. Regression analysis is a statistical technique that is very useful for these types of problems. Many applications of regression analysis involve situations in which there are more than one regressor variable. A regression model that contains more than one regressor variable is called a multiple regression model (Montgomery and Runger, 2007). Multiple linear regression analysis is usually used to summarize data as well as study relations between variables (Norusis, 1990). The multiple regression model can be formulated as follows:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_k X_k + \varepsilon \tag{1}$$

where: Y is the dependant variable or response, k is the number of independent or regressor variables, x_j is the independent or regressor variable, $j = 0, 1, \ldots, k$, β_j is the regression coefficient, $j = 0, 1, \ldots, k$, and $\mathcal{E}$ is a term that includes the effects of un-modelled sources of variability that affect the dependant variable.

Traditionally, multiple regression analysis has been used to model the functional relationships between anthropometric measurements. Meanwhile, in recent years, various methods based on artificial intelligence techniques are proposed as alternatives to statistical methods, especially to model highly nonlinear functional relationships (Kaya et al., 2003).

2.2.2. Neural network technique

In the last years, a great interest on the use of Artificial Neural Networks (ANNs) has grown. ANNs have been successfully applied to several problem domains, in areas such as medicine, engineering, geology, and physics, to design solutions for estimation problems, classification, control, etc. They can be used as predictive models because they are capable of modelling complex functions (Tronto et al., 2007).

A neural network represents a highly parallelized dynamic system with a directed graph topology that can receive the output information by means of a reaction of its state on the input actions (Galushkin, 2007). To achieve a good performance, neural networks employ a massive interconnection of simple computing cells referred to as “neurons” or “processing units” (Haykin, 1999).

A neuron is an information-processing unit that is fundamental to the operation of a neural network. Sigmoid function, whose graph is S-shaped, is normally used as activation function. The sigmoid function is by far the most common form of activation function used in the construction of ANN. It is defined as a strictly increasing function that exhibits a graceful balance between linear and nonlinear behaviour (Haykin, 1999).

“Behaviour” of a neural network has two aspects: processing tasks and learning or self-organization. A neural network reacts to signals, presented by the environment, by processing the presented input information in a manner meaningful to the network or network users. The network changes itself to process information meaningfully. The change in processing is mostly realized by the change in weight values (Hirose, 2006).

Learning is the change of the neural network, made by the network itself, in such a way that the resultant processing behaviour becomes in accordance with the wishes of network users. Typically, models of neural networks are divided into two categories in terms of signal transmission manner: feed forward neural networks and recurrent neural networks. They are built up using different frameworks, which give rise to different fields of applications (Hirose, 2006).

Multilayer Feed forward Neural Networks (FNNs), or equivalently referred to as multilayer Perceptrons (MLP), have a layered structure and process information flow in feed forward manner: an input layer consisting of sensory nodes, one or more hidden layers of computational nodes, and an output layer that calculates the outputs of the network (Tang, et al., 2007). FNN features a supervised training with a highly popular algorithm known as the error back-propagation algorithm (Hirose, 2006).

3. Materials and methods

A sample of 600 students voluntarily participated in this study. Students aged between 6 and 11 years old were randomly selected from five UNRWA-UNESCO primary male schools. 120 students were randomly selected from each school. Since a primary school consists of six classes, twenty students were selected from each class. The measurements were performed by two teams, each consisting of two people. Two Lafayette anthropometers along with a tape and adjustable sitting chairs were used to measure some of the anthropometric dimensions of these students. Specific details

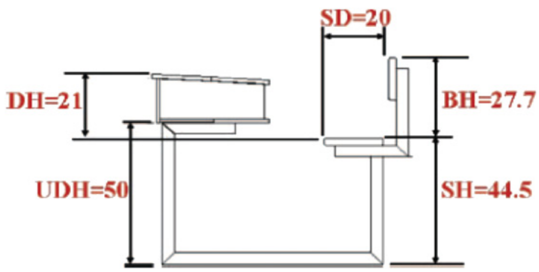

Fig. 1. Furniture dimensions (cm) showing the current UNRWA-UNESCO classroom furniture dimensions. SD = seat depth; BH = backrest height; SH = seat height; UDH = under-surface of desk height; DH = desk height.

on the measurements and participants in the study can be referred to in Agha (2010).

The four anthropometric dimensions, stature (*A*), shoulder-grip length (*I*), lower arm length (*J*), and shoulder breadth (*Q*) were used as inputs because they are easy to measure. Whereas the five anthropometric dimensions, shoulder height (*H*), elbow seat height (*K*), buttock popliteal thigh length (*M*), popliteal height (*N*), and knee height (*O*) were used as outputs because they are difficult to measure and yet they are needed for ergonomic design of school furniture. Fig. 1 shows the dimensions of the furniture used in the UNRWA-UNESCO schools in Gaza strip. Fig. 2 shows both input and output dimensions. From the Figure, it is clear that anthropometric dimensions, which are used as "inputs", can all be measured while students are standing. While those dimensions used as "outputs" require that students be sitting in a not so easy-to-control-position especially for children.

4. Linear regression model

Multiple linear regression is used to predict the anthropometric measurements. Minitab 14 Software (Ryan et al., 2005) is used to estimate the most important inputs for the regression equation. The "Best Subset Regression" is used for this purpose. Best subsets regression identifies the best-fitting regression models that can be constructed with the input variables specified. Best subsets regression is an efficient way to identify models that achieve goals with as few input variables as possible. Minitab examines all possible subsets of the input variables, beginning with all models containing one variable, and then all models containing two variables, and so on.

Coefficient of Determination (R^2) is a widely used measure for a regression model. It represents the amount of variability in the data explained or accounted for by the regression model. R^2 always increases if a variable is added to the model, but this does not necessarily imply that the new model is superior to the old one. Therefore, an adjusted (R^2) statistic is calculated. The adjusted (R^2) statistic essentially penalizes the analyst for adding variables to the model. Therefore, the adjusted (R^2) is an easy way to guard against over fitting, i.e., including variables that are not really useful (Montgomery and Runger, 2007).

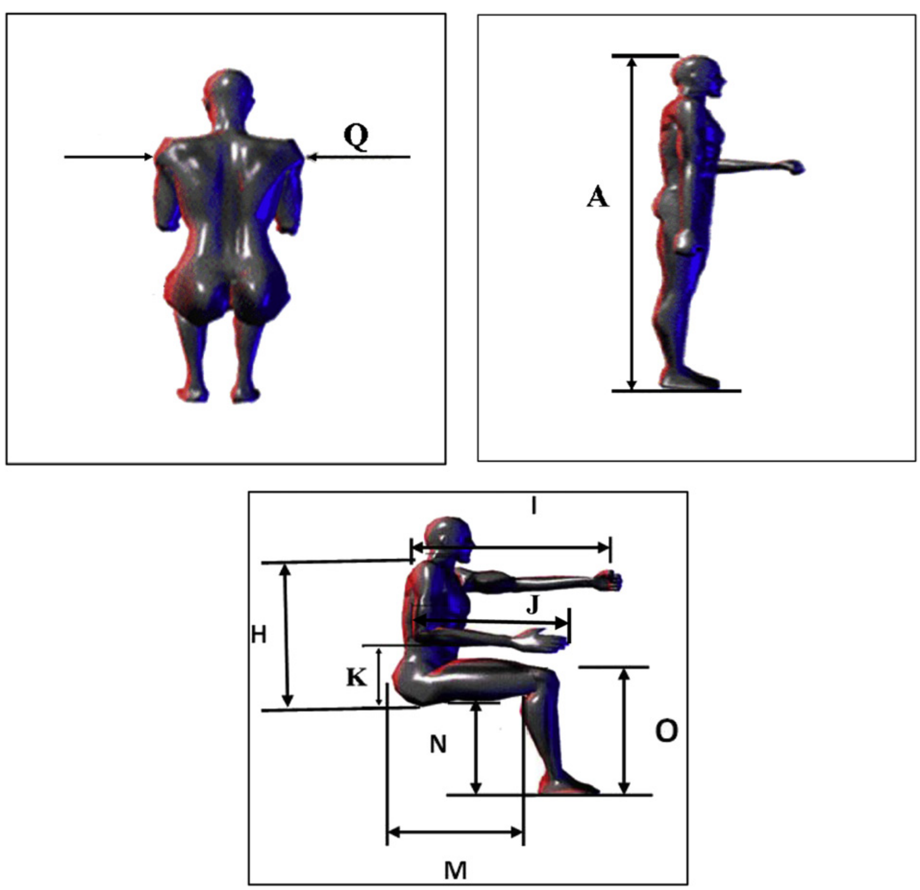

Fig. 2. Anthropometric Measures: stature (*A*), shoulder-grip length (*I*), Shoulder-grip length (*I*) and shoulder breadth (*Q*). The measurements that were taken as outputs are those that are usually used to ergonomically design the chair, which are shoulder height (*H*), elbow-seat height (*K*), buttock popliteal thigh length (*M*), popliteal height (*N*), and knee height (*O*).

Table 1
Best subset regression for the shoulder height (H). The bold row indicates the best fit subset of all.

Number of variables (Predictors)	Performance measures for regression				Inputs			
	R-Sq	R-Sq (adj)	Mallows C-p	S[a]	Stature (A)	Shoulder-grip length (I)	Lower arm length (J)	Shoulder breadth (Q)
1	75.3	75.2	9.5	2.0147	X			
1	65.6	65.5	246.3	2.3763			X	
2	**75.5**	**75.4**	**5.1**	**2.0057**	**X**			**X**
2	75.4	75.3	8.9	2.0120	X		X	
3	75.6	75.5	5.1	2.0040	X	X		X
3	75.6	75.4	6.0	2.0055	X		X	X
4	75.7	75.5	5.0	2.0022	X	X	X	X

[a] 'S is the square root of the Mean Square Error (MSE).

Another performance measure for the regression model is (C_p). It is desired that (C_p) be small and close to (p), where (p) is the number of coefficients (i.e., number of variables + 1 for models including an intercept). The values of (C_p) for each regression model under consideration are evaluated relative to p. The regression equations that have negligible bias will have values of (C_p) that are close to p, while those with significant bias will have values of (C_p) that are significantly greater than p (Montgomery and Runger, 2007).

A third performance measure for the regression model is (S) which is the square root of the Mean Square Error (MSE), thus, small values of (S) are desirable. Table 1 shows all possible combinations of input variables, A, I, J and Q that can be used to predict shoulder height (H). The Xs in the table represent the variable(s) used as input(s). It is noted from the table that shoulder height can be predicted using stature (A) only with adjusted (R^2) of 75.2, Mallows (C_p) of 9.5 and (S) of 2.0147. Further, it can be seen from Table 1 that shoulder height can be best predicted using stature (A), shoulder-grip length (I), lower arm length (J) and shoulder breadth (Q) as inputs because using these inputs will result in a model that has the highest adjusted (R^2), 75.5%, the lowest Mallows (C_p) value, 5.0, and the lowest (S) value, 2.0022. Eq. (2) is the best regression equation to predict (H):

$$H = 0.15 + 0.317\,A - 0.0765\,I + 0.0994\,J + 0.0910\,Q \qquad (2)$$

It can be seen that the equation contains minus sign before (I) which has no physical meaning. Adding (I) to the equation does not enhance the regression so much. As a matter of fact, its P-value is 0.086 which means that there is no strong evidence to conclude that it has a strong effect in explaining the variability in the data. The P-values for other inputs, A, J, and Q are 0, 0.15, and 0.033 respectively. Therefore, there is a strong evidence to support the claim that (A) and (Q) have significant effect. So the final model will contain only (A) and (Q). This model does not differ significantly from the model with all variables in Eq. (2) as it can be seen from Table 1 based on the four performance measures. The same process was done for all other outputs.

Multiple linear regressions were calculated for all inputs according to the best subsets regression found before. Table 2 shows each output as a function of the best inputs that can be used for its prediction. It is obvious from Table 2 that the expression for knee height (O) has the smallest (S) value, 1.1588, and the highest (R^2) value, 92.1%. Thus, it has the best regression equation of all. On the contrary, elbow seat height (K) has the worst regression equation. So it is advisable to measure the elbow seat height not to predict it.

To check the adequacy of the model regarding the normality assumption of the residuals and the constant variability, the probability plot of the residuals, and residuals versus fitted values were drawn for the model for all outputs and they all showed adequacy of the models.

5. Neural network model

NeuroSolution 5 software was used to get regression of the five outputs (desired values) using the four inputs. The study, using neural network, was conducted in two scenarios. The first scenario uses the same inputs as those selected by linear regression model. For example, the inputs used for predicting the (H) dimension are (A) and (Q). In the second scenario, all inputs combinations were tried until obtaining the best (optimal) combinations using neural network. It turned out that the two scenarios were identical. 60% of the data was used for training, 15% for crossvalidation, and 25% for testing. Before doing this, the arrangement of the rows of data was randomly changed to eliminate any effect of different classes on the results. That is; crossvalidation and testing data will not be from the same class of students.

Training is the process by which the free parameters of the network (i.e. the weights) get optimal values. During training, the input and desired data are repeatedly presented to the network. As the network learns, the error will drop towards zero. Lower error, however, does not always mean a better network. It is possible to over train a network. Crossvalidation is a highly recommended criterion for stopping the training of a network. After training a network for 1000 epochs, the network performance is tested using data that was not used in network training process.

Table 3 shows the results of neural network prediction. It represents the neural network analysis where the inputs are the same as those used in linear regression.

After that, the optimal selection of the inputs was found by trying all the possible combinations of the inputs until the best

Table 2
Linear regression equations for anthropometric measurements.

Output	Regression equations	S	R^2 (%)
Shoulder height (H)	$H = 0.45 + 0.310A + 0.105Q$	2.00568	75.5
Elbow seat height (K)	$K = -1.37 + 0.0879A + 0.176Q$	2.24659	26.4
Buttock popliteal thigh length (M)	$M = -6.92 + 0.272\,A + 0.161I$	2.06052	75.3
Popliteal height (N)	$N = -4.23 + 0.204\,A + 0.138I$	1.72526	72.1
Knee height (O)	$O = -7.30 + 0.270A + 0.109I + 0.210J$	1.15881	92.1

Table 3
Neural network regression analysis.

Output	Input	S	R^2
Shoulder height (H)	Stature (A), shoulder breadth (Q)	1.83719	74.7
Elbow seat height (K)	Stature (A), shoulder breadth (Q)	1.21107	25.1
Buttock popliteal thigh length (M)	Stature (A), Shoulder -grip length (I)	1.77827	75.7
Popliteal height (N)	Stature (A), Shoulder -grip length (I)	1.42947	71.9
Knee height (O)	Stature (A), Shoulder -grip length (I), and Lower arm length (J)	1.09092	92.1

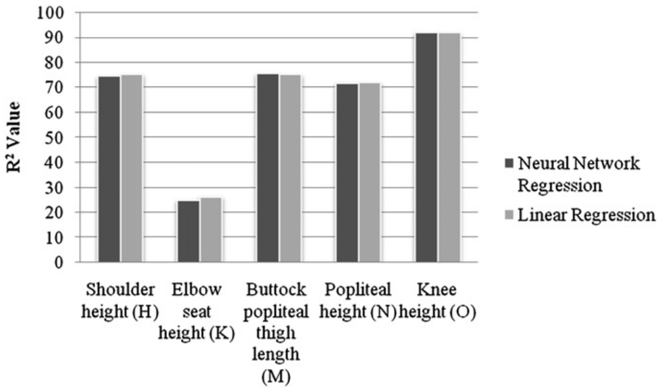

Fig. 3. Comparison between multiple linear and neural network regression based on R^2 value for the needed anthropometric dimensions.

solution (minimum values of (S) and maximum values of (R^2)) is obtained. The optimum solution was found to be identical to the results in Table 3. This means that the optimum inputs of the two models, linear regression and neural network, are the same. In the two models, it is noted that elbow seat height (K) is difficult to predict accurately.

A comparison between the linear regression and optimum neural network regression is shown in Figs. 3 and 4. It is obvious from Fig. 3 that the performances of linear regression and neural network regression are almost the same based on (R^2) value. Further, Fig. 4 clearly shows that the performance of neural network generally behaves better than linear regression, based on (S) value. So, generally, neural network is better than linear regression in predicting anthropometric measurements.

Currently, the school furniture design is the same for all students in all classes. It is clear that it is not right. A study by Agha (2010) proposes two different designs of school furniture, the first is for classes from one to three and the second is for classes from four to six. The two models of this study, linear regression and neural network regression, can be used to predict the critical dimensions for determining these two designs or if there are other approaches that may contain more than two designs.

The study showed that the neural network model is better than linear regression in predicting the required dimensions. So if the linear regression model is adequate, then the neural network model will be adequate. Therefore, in this study, the main concentration will mainly be on testing the adequacy of linear regression. To compare between the actual and predicted dimensions, the equations found in Table 2 were used to predict the five output dimensions for each of the 600 students. Then these predicted values were compared to the actual values using the means and standard deviations. The means and standard deviations of the actual and predicted shoulder height (H) for all the students in the six classes are shown in Table 4. It is obvious that they are almost the same. To be sure that the differences between them are not significant, two-sample t-test was conducted in Table 5. The P-values were calculated using Minitab 14 software. All the P-values for (H) are greater than 0.05 which means that there is no significant difference between the actual and the predicted means for any of the six classes. Now let's consider the (K) dimension. As stated before, this dimension is poorly related to the inputs where the values of (R^2) in the two models were very low. However most of the actual and predicted means as can be seen from Table 4 and Table 5 are very close to each other. Actually, only class 4 and class 6 have significant differences between the actual and predicted means. The same two-sample t-test was done for all other dimensions, and the results revealed similarities in the means of actual and predicted dimensions for each class.

Table 4
Comparisons between actual and predicted means and standard deviations for H and K.

Variable	Predicted H[a]		Actual H		Predicted K[a]		Actual K	
Class	Mean	StDev	Mean	StDev	Mean	StDev	Mean	StDev
1	39.834	1.909	39.636	2.636	13.843	0.804	13.787	2.377
2	41.867	2.079	42.239	2.886	14.705	0.838	14.679	2.471
3	43.565	2.224	43.453	3.123	15.205	0.920	15.367	2.226
4	44.989	1.879	44.458	2.760	15.690	0.773	15.192	2.168
5	46.542	2.518	46.718	2.890	16.287	1.058	16.040	2.481
6	48.116	2.263	48.612	2.541	16.901	0.947	17.589	2.315

[a] Prediction of shoulder height (H) and elbow seat height (K) was done based on linear regression model.

However, the ergonomic design of furniture usually depends on tolerance limits such as 1–99% of population. Therefore, for the model to be adequate for design purposes, the percentiles of actual and predicted dimensions should be close together. This study used the system used in the study by Agha (2010) where two designs of the furniture were proposed, one for classes from 1 to 3 and the other design for classes from 4 to 6. So, the tolerance intervals need to be estimated for these two groups of classes for the five output dimensions. Table 6 shows the tolerance interval based on Eq. (3). A tolerance interval for capturing at least γ% of the values in a normal distribution with confidence level 100 $(1-\alpha)$% is

$$\bar{x} - ks, \quad \bar{x} + ks \tag{3}$$

where k is a tolerance interval factor found in special tables, and $\bar{x}$ and s are average and standard deviation of the sample respectively (Montgomery and Runger, 2007). In Table 6, γ was determined to be 99%. As it is obvious from the table, except for (K), the percentiles were very close together. To be sure, paired t-test was used, and

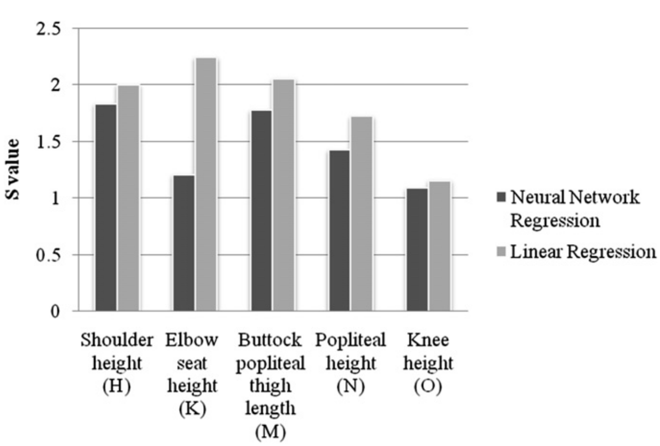

Fig. 4. Comparison between multiple linear and neural network regression based on S-value for the needed anthropometric dimensions.

Table 5
P-values of two-sample t-test to investigate the differences between actual and predicted means of H and K.

	Class 1	Class 2	Class 3	Class 4	Class 5	Class 6
H vs. Predicted H[a]	0.544	0.297	0.771	0.114	0.647	0.147
K vs. Predicted K[a]	0.824	0.921	0.502	0.032[b]	0.361	0.007[b]

[a] Prediction of shoulder height (H) and elbow seat height (K) was done based on linear regression model.
[b] Only for class 4 and class 6, there were significant differences between predicted and actual (K) values.

Table 6
Tolerance intervals of actual and predicted dimensions.

Dimension	Classes	Predicted dimensions		Actual dimensions	
		Lower limit (P1)	Upper limit (P99)	Lower limit (P1)	Upper limit (P99)
Shoulder height (*H*)	1–3	49.7	54.5	52.0	56.5
	4–6	33.8	38.6	31.6	36.7
Elbow seat height (*K*)	1–3	17.7	19.6	22.2	24.1
	4–6	11.4	13.0	7.1	8.5
Buttock popliteal thigh length (*M*)	1–3	41.8	46.9	42.9	48.4
	4–6	25.8	30.7	24.0	29.9
Popliteal height (*N*)	1–3	33.3	37.2	34.1	39.0
	4–6	20.9	24.7	19.5	23.2
Knee height (*O*)	1–3	46.8	52.3	46.7	52.7
	4–6	29.1	34.5	28.7	34.3

results revealed closeness between actual and predicted percentiles with *P*-value of 0.872. This clearly indicates the adequacy of the models.

6. Conclusions

To ergonomically design chairs, five anthropometric dimensions are necessary. These dimensions are usually not easy to measure. However, they can be predicted through models such as linear regression and neural network using easy-to-measure dimensions. Four anthropometric measures were used as inputs due to their ease to be measured where they can all be measured while the person is standing. A comparison was made between neural network and linear regression for predicting the anthropometric measurements. By considering (R^2) only, the two models are almost the same; and by considering (S) value, all the measurements are better predicted by neural network. Generally, neural network is better than linear regression in predicting anthropometric measurements needed for ergonomic chair design.

In this study, only four anthropometric dimensions were chosen as inputs. Future studies may consider other input dimensions which may lead to better performance in predicting output dimensions. Future studies may focus on prediction of female body dimensions which may lead to models with different parameters.

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