An Application of Data Mining Technique in Developing Sizing System for Army Soldiers in Taiwan

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Abstract: - In the field of garment manufacturing, the planning and control of production and inventory are rather complicated procedures. This is the reason that establishing standard sizing systems is necessary and important for garment manufacturers in Taiwan. As the standard sizing systems need anthropometric data for reference, an anthropometric database for Taiwan army servicemen was first constructed for the purpose of simplifying the entire process. Anthropometric data collected from scratch are used to establish the sizing systems. The data mining method, which has been extensively used in many fields, is applied in this project. Few researches have been conducted in addressing the establishment of sizing systems. This study aims to establish systems for determining the sizes of garments for army personnel using the data mining technique. The newly developed sizing systems can be adopted to better accurately predict the requirements of different sizes of uniforms, and then to generate a practical production planning procedure. This study found that, by applying data mining technique, unnecessary inventory costs resulting from sizing mismatches that portend large differences between the numbers of soldiers and of produced garments can be significantly minimized.

Key-Words: - Anthropometric data, Data mining, Decision tree, Sizing systems, Production planning, Garment manufacturing

1 Introduction

Anthropometry is a knowledge of body dimension measurement. Due to the growing importance of the anthropometric database, a large number of anthropometric surveys and studies have been carried out since the end of World War II. Many developed countries have devoted great efforts to establish anthropometric databases for specific groups of people, such as truck drivers, children, aged people, laborers, civilians, the military personnel and etc. [1][2][3][4]. Anthropometric data have been used for some years in order to provide body size information in research and development. Body size and body proportions are essential for safety and healthy in work environment, such as workstation and facility layout, personal equipment design and garment sizing system development.

Garment manufacturing is the highest value-added industry in the textile industry’s manufacturing chain [5]. Increasing global competitiveness presents difficult challenges for businesses in the garment industry [6]. Mass production by machinery in the garment industry has replaced manual manufacturing, so the planning and control of production and inventory are very important for manufacturers. Moreover, this type of manufacturing follows certain standards and specifications and each country has its own standard sizing systems for manufacturers to follow and fit in with the figure types of the local population. Standard sizing systems can correctly predict manufacturing quantity and the proportion to the physique, resulting in more accurate production planning and better control of materials [7] [8]. The standard sizing systems have been used as a communication tool among manufacturers, retailers, and consumers. It provides manufacturers with size specification, design development, pattern grading and market analysis. Manufacturers, basing their judgments on the information, can produce different types of garments with various allowances for specific market segments. Thus, establishing standard sizing systems is necessary and important.

Garment sizing systems were originally developed by tailors in the late 18th century, before which all garments were hand-made to order. Tailors measured the body dimensions of each customer, and then drew and cut patterns for each garment. This method yielded the most satisfactory fitting possible, but was only suitable for individuals whose body dimensions had been measured. After enough original patterns had been accumulated, tailors discovered correlations between bodily dimensions, regardless of the individual differences. Tailors gradually developed these patterns into a system of storing garments, which could be used to make clothes for people with similar figures [9] [10].

Emanuel (1959) derived a set of procedures for formulating standard sizes for all figure types. According to his system, people with any type of figure were first classified into one of four bodyweight groups. These groups were subdivided into two categories specified by body height - short and tall [11]. People were thus divided into eight categories of similar heights and weights. The sizing systems in most countries were similar, and classifications were based on two or three sizing variables. The female sizing systems in Britain, for example, uses two sizing variables, bust girth and hip girth; Germany uses three sizing variables, body height, bust girth and hip girth; and so does Japan [12] [13]. The sizing variables commonly used for male clothing are body height, chest girth and waist girth; the sizing variables for female clothing are typically body height, bust girth and hip girth [14] [15].

McCulloch et al. (1998) proposed the criteria that follow, by which good sizing systems could be evaluated [16].

- The fewest number of sizes,
- The greatest number of people to be covered by the sizing systems.

These criteria sometimes conflict with each other, but which one should take higher priority depends on the type of garment and the needs of the customer.

2 Data Mining and Decision Trees

Fayyad (1997) defined knowledge discovery in databases (KDD) as the nontrivial process of identifying valid, novel, potentially useful and ultimately understandable patterns in data [17]. Berry and Linoff (2000) defined data mining as the analysis of a huge amount of data by automatic or semi-automatic means to identify significant relationships and rules. Data mining has been extensively used as a major step of KDD [18]. It has been successfully applied in many fields, such as manufacturing [19], job shop scheduling [20], biomedicine [21], health insurance [22], finance [23] and the prediction of country investment risk [24]. However, research on establishing sizing systems using data mining is lacking.

The decision tree technique is an important method of data mining. Its main function is to classify data according to the rules deduced from input variables, displaying them in a tree-shaped form and then exploring factors of significant influence. The technique is strongly suited to data mining. The decision tree provides the following advantages [18] [25].

- The rules it produces are easy to understand.
- The classification does not require much calculation.
- It can process both discrete and continuous data.
- It clearly indicates the most important variables in a classification.

Data can be divided into two types: discrete and continuous. Different decision tree algorithms suit different types of data. Among the available algorithms, the classification and regression tree (CART) is the most appropriate method for generating a decision tree for processing continuous data [26] [27]. Since anthropometric data is continuous, this research employs CART as the classification tool for use in data mining.

CART uses a tree-shaped structure to classify data into categories. Its basic principle is to put the pre-processed data into the root of a tree, and then, by performing a series of classifications, finds the best separating points, forming a tree-shaped structure. The classification rules separate the data according to the purity or impurity of the child nodes. These rules incorporate the valuable information gleaned by mining the data and these can be fully used in data classification [28].

The most important property of CART is that it can reduce the complexity of the decision tree, including its depth and the number of child nodes, while enhancing the accuracy of classification. The key to a CART algorithm is to identify important attributes - predictive variables - by considering which target variables can be divided into a number of child nodes. Each splitting reduces the impurity of the child nodes, until the samples in every child node are of the same type [29].

This study attempts to explore and analyze a large amount of anthropometric data using decision tree-based data mining. In particular, the CART technique is used to identify significant patterns based on which of the figures of Taiwan military personnel can be classified and to establish the standard sizing systems. The newly developed sizing systems will be established according to the four working cycle of data mining.

3 Anthropometric Survey

For the anthropometric survey, 265 static anthropometric variables, including both standing and sitting postures, were measured from 610 army soldiers with age ranging from 19 to 35 years old. Three equipment were used for static measurements, i.e. a three-dimensional (3-D) coordinate measurment probe, a digital caliper and an digital tape measure. The 3-D coordinate measurment probe and the digital caliper were used to measure the liner dimensions, the tape measure was used for measuring either body contours or the lengths of body curvatures. All equipment were calibrated with accuracy level up to 0.1mm [30].

Thirty-eight major anthropometric dimensions that are commonly considered in work and clothing design were selected in this study. The means, standard deviations and the 5th and 95th percentiles of the thirty-eight dimensions for Taiwan's army soldiers are presented in Table 1.

Table 1.
The anthropometric data of army soldiers (ages 19-35) in Taiwan (mm)

	Mean	Std	5th%ile	95th%ile
Stature	1702.3	55.3	1611.8	1796.7
Eye height	1595.0	56.2	1505.7	1688.6
Waist height	1004.2	42.3	936.0	1070.2
Crotch height	743.9	42.6	675.1	816.5
Shoulder height	1395.5	50.0	1311.9	1477.5
Shoulder width	380.1	21.1	347.1	412.7
Chest width	316.6	16.0	291.5	344.2
Arm length	743.6	32.7	689.4	798.5
Elbow height	1055.7	39.2	992.6	1119.8
Elbow to grip length	313.7	19.1	282.9	342.7
Vertical reach	2139.4	77.6	2006.7	2269.2
Cervical height	1424.7	51.0	1343.6	1510.1
Sitting height	906.1	27.5	859.5	951.3
Eye height, sitting	786.6	27.4	742.3	832.0
Knee height, sitting	524.7	25.0	485.9	567.4
Popliteal tendon height, sitting	410.3	19.2	380.3	441.6
Elbow height, sitting	259.9	24.2	219.8	299.5
Vertical reach, sitting	1346.0	47.8	1270.5	1425.0
Buttock to front of knee, sitting	567.1	27.4	522.9	614.4
Buttock - popliteal length, sitting	461.6	25.7	421.0	504.8
Waist front	361.2	31.4	312.3	413.8
Sleeve length	615.6	32.4	559.6	668.2
Waist back	439.8	33.2	385.4	493.4
Chest girth	871.6	55.4	787.9	976.8
Waist girth	737.4	62.4	652.5	859.9
Abdominal girth	771.6	62.1	684.3	887.5
Hip girth	906.9	54.9	820.5	1003.2
Forward reach	830.4	37.7	770.0	895.3
Head girth	565.1	16.7	537.7	591.4
Neck girth	361.2	21.9	326.6	398.4
Wrist girth	170.2	12.5	150.3	193.2
Crotch length	640.4	39.4	580.1	709.2
Head breadth	163.4	6.8	152.6	174.1
Back width	500.5	48.3	413.6	573.3
Elbow to elbow breadth	404.4	45.8	328.2	484.4
Hip breadth, sitting	332.4	24.1	295.2	375.5
Chest thickness	209.5	17.7	184.4	240.7
Weight (kg)	64.7	8.5	52.7	80.2

4 The Data Mining Procedure

4.1 First step of data mining: defining the problem

Because the current standard sizing systems for soldiers' uniforms were outdated and incomplete, an updated database including anthropometric data of 610 soldiers was used. For each individual, 265 static anthropometric variables were involved, resulting in a total of 161,650 data. This study analyzes a large amount of data by applying the decision tree approach to data mining, and identifies systematic patterns in bodily dimensions. Based on these patterns, the representative figure types of Taiwan army soldiers are classified, upon which the standard sizing systems can be established. The army soldiers' database is selected for developing sizing systems because of the urgent need for accurate sizing systems for producing army uniforms. This work will be beneficial to the production of military uniforms in Taiwan.

4.2 Second step of data mining: preparing and analyzing data

The processing and conversion of the data increase the efficiency and ensure the accuracy of its analysis. Before the data are mined, they must be examined and purified. In this study, all the missing or anomalous data were omitted. Consequently, among the 610 samples gathered from the army soldiers, the 8 samples with missing or abnormal data were excluded, leaving a total of 602 valid samples for further processing. Because all these dimensions are measured in millimeters with decimals, they were transformed into integers in centimeters, for comparison with commonly used international garment-sizing units. Additionally, the two anthropometric variables, body weight and body height, were transformed into a new variable, the body mass index (BMI). This was used as the target variable of the decision tree, to facilitate data mining. The World Health Organization defines BMI as body weight divided by body height squared. It is used in medical science as a reference for judging obesity-related diseases and whether a figure type is standard or not. The Taiwan military also refere to BMI between 16.5 and 32 as a criterion to determine qualified military personnel.

Not all of the 265 anthropometric variables are useful for establishing garment-sizing systems; therefore the bodily dimensions commonly adopted by the garment manufacturing sector are first considered. Domain experts were consulted to identify 12 anthropometric variables that are strongly associated with garment production.

It would be a very complicated task using all 12 anthropometric variables to establish sizing systems. Therefore, factor analysis was applied herein to extract the important factors. According to Kaiser's eigenvalue criterion, two factors whose eigenvalues are over one were selected [31]. Then, factor loadings were calculated to determine the correlation coefficients between the two factors and the anthropometric variables. The anthropometric variables with factor loadings of over 0.7 were found to be clustered in Factors 1 and 2, as shown in Table 2. Most of the variables that appeared in Factor 1 were girth-related variables, including chest girth, waist girth, hip girth, neck girth, chest width, shoulder width and body weight. The variables appeared in Factor 2 were height-related variables, including body height, cervical height and arm length. Accordingly, Factor 1 was called the girth factor, and Factor 2 was called the height factor.

Table 2.
Factor loading after varimax rotation

	Factor 1	Factor 2
Chest girth	0.887*	0.103
Waist girth	0.885*	0.113
Hip girth	0.867*	0.229
Neck girth	0.712*	0.107
Chest width	0.859*	0.113
Back width	0.530	0.114
Shoulder width	0.859*	0.110
Body height	0.138	0.943*
Cervical height	0.142	0.940*
Back waist length	0.192	0.531
Arm length	0.215	0.719*
Body weight	0.874*	0.317
Variance explained	5.472	2.798
Total proportion	0.456	0.233

* loadings > 0 .7

The results of factor analysis presented in Table 2 show that, besides body weight, the top three anthropometric variables that were most closely correlated with the girth factor were chest girth, waist girth and hip girth. Chest girth is the anthropometric variable most closely correlated with the girth factor, in the field of garment making, chest girth is also the most important variable in establishing sizing systems [12] [13]. Therefore, chest girth is selected to represent the girth factor. Body height is the anthropometric variable correlated most closely with the height factor so body height was selected to represent the height factor.

4.3 Third step of data mining: data mining by a decision tree technique

Following Step 2, the chest girth and body height were selected as the most important sizing variables. Then, data were mined by applying the CART decision tree technique. BMI is a comprehensive index of body weight and body height. This study adopts BMI as the target variable. Chest girth and body height are the predictive variables for classifying the target variable. The following stopping rules are set as follows.

- The greatest depth of the tree extends to the third level beneath the root node.
- The minimum number of samples in the parent node is 100, and that in the child node is 40.

Figure 1. shows the results of CART analysis, from which the classification rules can be identified. The root node was split according to the chest girth, resulting in the first level. A total of 401 samples whose chest girth were smaller than or equal to 88.5 cm were grouped into Node 1, and 201 samples with chest girth greater than 88.5 cm were grouped into Node 2.

Then Node 1 was split according to chest girth to yield the second level of the tree. One hundred fifteen samples with chest girth of less than or equal to 82.5 cm, were grouped into Node 3, and the other 286 samples, whose chest girth exceeded than 82.5 cm, were grouped into Node 4. Node 2 was also split similarly: 133 samples with chest girth of less than or equal to 94.5 cm were grouped into Node 5, and the other 68 samples with chest girth of over than 94.5 cm, were grouped into Node 6.

The first 2 levels were according to chest girth. From the third level, body height was used for splitting. However, only the four nodes generated at the second level were selected to represent the four figure types and thus to reduce the number of figure types.

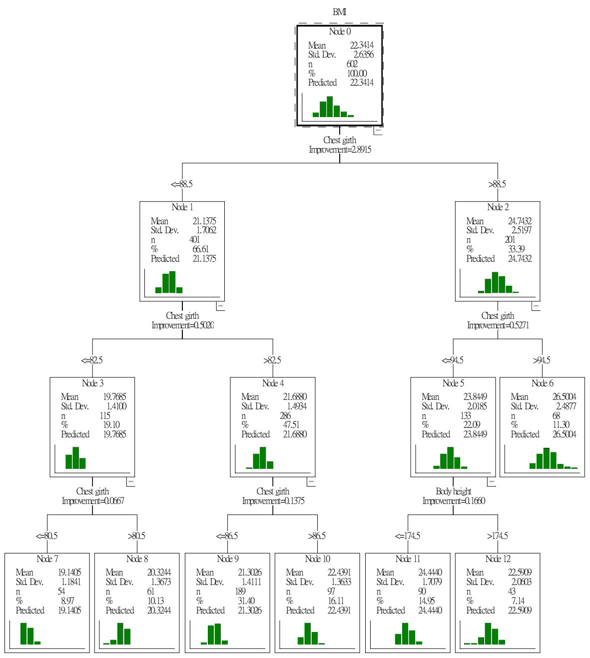

Fig. 1.
CART branching

Figure 2 plots a distribution graph of chest girth as the X-axis against waist girth on the Y-axis to demonstrate the distribution of all figure types. Waist girth is also an important variable for sizing male garments in many countries and it significantly correlates with the girth factor. This study identifies the figure type of 115 people with smaller chest girth and waist girth as Small; that of 286 samples as Medium; that of the 68 samples with larger chest girth and waist girth, as Extra Large, and that of the remaining 133 samples, as Large. Table 3 presents these results.

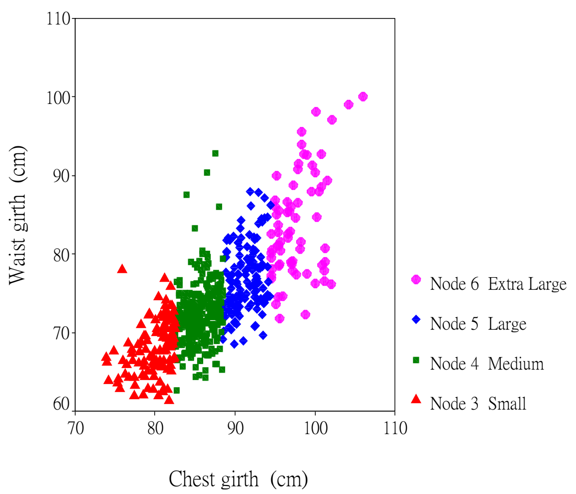

Fig. 2.
Scatter plot of chest girth vs. waist girth for four figure types

Table 3.
Definitions of four figure types

Node	Figure type	Classified rule	Number
3	S	Chest girth ≦ 82.5 cm	115
4	M	82.5 cm ＜Chest girth ≦ 88.5 cm	286
5	L	88.5 cm ＜Chest girth ≦ 94.5 cm	133
6	XL	94.5 cm ＜Chest girth	68

4.4 Fourth step of data mining: discussion and application of the results

A line graph was plotted to yield a better insight into the differences among the four figure types classified by CART. The average anthropometric variable values was drawn for the four figure types. As shown in Figure 3, the four figure types are exhibited by clear differences in chest girth, waist girth and hip girth.

The four figure types also follow the order XL>L>M>S. The ANOVA results and Duncan’s multiple range tests also indicated the significant differences among the four figure types.

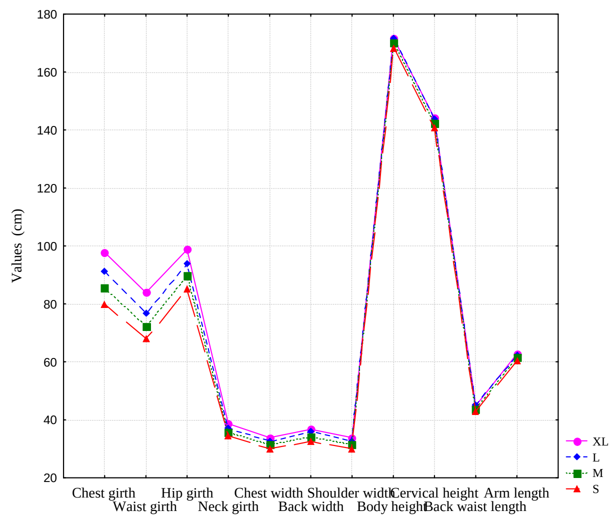

Fig. 3.
Four figure types and corresponding anthropometric variables

4.5 Establishing the sizing systems

Once the four figure types were classified by CART, this section shows the relevant scatter plots of chest girth on the X-axis against waist girth on the Y-axis and the interval was 4 cm. The chest girth are set as follows.

- 78 cm and 82 cm for the S figure;
- 86 cm for the M figure;
- 90 cm and 94 cm for the L figure;
- 98 cm and 102 cm for the XL figure.

The four figure types are discussed separately, to establish respective sizing systems according to the methods of Emanuel.

Figure 4 presents a scatter plot for the S figure of waist girth on the Y-axis against chest girth on the X-axis; the range of chest girth was from 74 cm to 82 cm. Most countries use 4 cm as the interval of chest girth [32]; so the chest girth of 78 cm and 82 cm were used for the S figure. Figure 4. shows a scatter plot of 115 samples of the S figure. The scatter plots of the other types of figures are similar to that of the S figure type. Table 4 presents complete sizing systems for all four figure types. Among all of the 602 samples, only 24 samples that fell outside of the meaningful range were excluded. Therefore, the coverage of the proposed “chest girth and waist girth” sizing systems was 96%.

	Sum	3	3	5	8	6	13	16	25	36	115
	78			1							1
	77								**1**		1
	76									**1**	1
	75							**1**			1
	74								**1**		1
	73								**2**	**3**	5
	72						**2**	**1**	**3**	**6**	12
	71					**1**			**3**	**1**	5
	70						**2**	**2**	**3**	**4**	11
Waist girth (cm)	69				**1**	**1**	**1**		**1**	**10**	14
	68		**1**		**1**	**2**	**1**	**1**	**3**	**3**	12
	67	1			**1**		**1**	**1**		**2**	6
	66	1		**2**	**1**	**1**	**2**	**6**	**5**	**2**	20
	65			**1**		**1**	**1**	**1**		**2**	6
	64	1	**2**		**2**		**1**	**1**	**1**		8
	63			**1**	**1**		**2**	**1**	**2**	**1**	8
	62				**1**			1			2
	61									1	1
		74	75	76	77	78	79	80	81	82	Sum
		Chest girth (cm)									

Fig. 4.
Scatter plot for S-figure

When three sizing variables - chest girth, waist girth and body height - are taken into account, the total coverage of the military garment-sizing systems is 89%. The army soldiers’ garment-sizing systems that use three variables of chest girth, waist girth and body height can be established as shown in Table 4.

Table 4.
Garment-sizing systems for army soldiers with four types of figures

	Body measurements in cm		Body height in cm			
Figure type	Chest girth	Waist girth	Short (162 -169)	Tall (170 -178)	%	Drop
S	**78**	**64**	—	174	1.2	**14**
		68	166	174	1.9	
		72	—	174	0.5	
	82	**66**	166	174	4.9	**16**
		70	166	174	6.1	
		74	166	174	3.8	
		78	—	174	0.5	
M	**86**	**68**	166	174	4.9	**18**
		72	166	174	15.3	
		76	166	174	9.5	
		80	166	174	2.1	
	88	**70**	166	174	2.6	**18**
		74	166	174	7.9	
		78	166	174	4.9	
		82	—	174	0.5	
L	**90**	**72**	166	174	2.3	**18**
		76	166	174	3.5	
		80	166	174	2.1	
		84	166	—	0.9	
	94	**74**	166	174	3.1	**20**
		78	166	174	5.4	
		82	166	174	3.5	
		86	166	174	1.6	
		90	—	174	0.5	
XL	**98**	**76**	—	174	0.7	**22**
		80	—	174	2.3	
		84	166	174	2.1	
		88	166	174	1.7	
		92	—	174	0.7	
	102	**78**	—	174	0.9	**24**
		82	—	174	0.5	
		90	—	174	0.9	
		94	—	174	0.7	

4.6 Evaluating the sizing systems

As described above, four figure types are obtained by using the classification rules based on the decision tree technique of data mining. The newly developed sizing systems exhibit the following three characteristics:

(1) High coverage rates and few sizing groups
As stated above, the coverage of the sizing systems that use the two sizing variables (chest girth and waist girth) is 96%. If body height is added to each figure

type, the total coverage rate is still 89%. The obtained sizing systems include 53 groups, fewer than those in many other countries, such as 60 in Germany; 72 in Japan; 102 in Finland; 202 in England, and 307 in France[14].

(2) Regular patterns and rules
The sizing systems, like sizing systems in other countries, have regular patterns and rules. They use 4 cm as the interval for both chest girth and waist girth: the chest girth is 78 cm and 82 cm for the S figure; 86 cm for the M figure; 90 cm and 94 cm for the L figure and 98 cm and 102 cm for the XL figure. Another size of 88 cm was added because most individuals are found to have M figure type.

The first corresponding waist girth for each figure type is presented in order. They are: 64 cm and 66 cm for the S figure; 68 cm and 70 cm for the M figure; 72 cm and 74 cm for the L figure and 76 cm and 78 cm for the XL figure type. The regularity found in the waist girth classification is also obvious.

The drop value is the difference between chest girth and waist girth and it can be obtained by subtracting the chest girth for each figure type from its first matching waist girth. For example, the chest girth is 78 cm for the S figure type and the waist girth is 64 cm; the chest girth of the S figure type is 82 cm and the waist girth is 66 cm, and so on. The resulting drop is 14 cm and 16 cm for the S figure; 18 cm for the M figure; 18 cm and 20 cm for the L figure and 22 cm and 24 cm for the XL figure type. Table 4 shows a clear regular pattern and rule.

(3) Providing manufacturers with references to facilitate manufacturing
The newly developed sizing systems fit very well with the practice of garment making. Table 4 can serve as a reference for production planning. The obtained sizing systems use the ISO labeling method. For example, 82LT means that the waist girth is 82 cm, the figure type is L, and the body height is “tall” (174 cm). Table 4 shows that the corresponding chest girth is 94 cm. Thus, the details of the body dimensions of soldiers can be obtained using easy-to-understand sizing systems. The percentages of the number of soldiers who belong to certain figure types and sizes are also recorded in the sizing systems, serving also as a good reference to indicate the quantity of garments to be produced for a specific market. Thus, a realistic plan for producing male soldiers’ uniforms can be established. Manufacturers, basing their judgments on the sizing systems, can make different type of garments with various quantities.

5 Conclusions
This study applies decision tree-based data mining to developing sizing systems for army soldiers in Taiwan. The obtained systems exhibit the following advantages.

- The sizing systems based on the decision tree show regular patterns and rules.
- The total applicability of the sizing systems was 89%, which is relatively high.
- The number of the size groups is at 53, fewer than those in many other countries. The obtained systems for sizing soldiers’ uniforms can be used as a communication tool among garment manufacturers and the military logistic management offices.

The newly developed sizing systems for army soldiers’ uniforms can correctly predict the requirements of different sizes of uniforms, and thus to generate a practical production plan. Unnecessary inventory costs resulting from sizing mismatches that portend large difference between the numbers of soldiers and produced garments can be significantly minimized.

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