Identification of Learners' Attitudes Toward Statistics Based on Classification of Discriminant Function

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Abstract: - This study had identified the profiles of statistics learners' attitude toward statistics through the classification process of discriminant function. This multivariate technique method is used to profile the subjects' attitude into either positive or negative attitude towards statistics. The study had characterized each profile of learners by relating to his/her perceived attitudes toward statistics, types of learners, mode of study, programme structure, age, gender and learners' evaluation towards the statistics course. Learners' attitudes toward statistics were measured using the Attitudes Toward Statistics (ATS) instrument which comprised four sub-scales or dimensions, namely, Affect, Cognitive Competence, Value and Difficulty. These variables are examined as predictors that discriminate learners with positive and negative attitudes toward statistics. The results indicate that learners with positive attitudes can be reliably distinguished from learners with negative attitudes toward statistics across the four ATS sub-scales, types of learners, mode of study and learner's evaluation towards the course. The results would assist instructors to fine-tune their teaching methodologies to optimize the teaching and learning of statistics in the classroom.

Key-Words: - Discriminant function, statistics learners, attitudes toward statistics, profiles

1 Introduction

What distinguishes a statistics learner with a positive attitude towards statistics from a learner with a negative attitude towards statistics? Does each type of learner have a different profile of attributes? This study attempts to construct profiles of two types of statistics learners - those with a positive attitude towards statistics and those with a negative attitude towards statistics. The process involves identifying the predictors that discriminate between learners with a positive attitude and learners with a negative attitude toward statistics. This study attempts to characterize the profile of each learner by looking into their perceived attitudes toward statistics based on Schau's Attitude Towards Statistics (ATS) instrument [1] which comprised four dimensions (Affect, Cognitive Competence, Value, Difficulty), types of learners, mode of study, program structure, area of study, age, gender and the learner's evaluation towards the statistics course.

2 Related Studies on Attitudes Toward Statistics

Studies on attitude towards statistics have been conducted in various parts of the world and different aspects of attitude surveys were reported [1], [2]. However, most studies were confined within their own respective courses. The challenge in conducting such studies is the ability to measure the students' attitude across several disciplines prior to their enrolment in any introductory statistics course.

Many statistics educators and most statistics students believe that attitudes toward statistics are important in the learning process. Schau [3] discovered that students attributed their positive change towards the learning of statistics to the attitudes of their instructors/teachers. They attributed their negative attitudes at the beginning of the statistics classes to poor teaching that eventually led to poor achievement in mathematics.

In a previous study, attitudes toward statistics and course achievement causally impact each other [2]. Schau [3] defined Prior Attitudes and Prior Achievement as exogenous variables where students who enter classes already possess attitudes toward statistics and learning that will impact their course performances. Attitudes and Course Achievement are endogenous variables that impact each other throughout the course and are impacted by both Prior Attitude and Prior Achievement.

There is also a growing interest among statistical education researchers on the extent of the relationship between the attitude dimensions (Affect, Cognitive Competence, Value and Difficulty) and the students' profile such as age, gender, mathematics and statistics achievement [4], [5]. It is also of concern to several researchers to determine which dimensions of attitude subscales are expected to impact on the statistics course performances [6], [7].

Mill [8] revealed that undergraduate students who enrolled in an introductory undergraduate statistics course at a large southeastern university in the College of Business have more positive attitudes toward statistics, a finding that coincides with several prior researches [9], [10]. However, to a certain extent a small number have indicated less than positive attitudes, i.e. students agreed that they get frustrated over statistics tests in class, that statistics is a complicated subject, that it requires a great deal of discipline, that it is highly technical, and that it is not a subject quickly learned by most people.

An examination of the cross tabulations of the gender variable provided the most interesting results. It was depicted that males were more likely than females to report that they were not scared of statistics, that they can learn statistics, and they felt confident mastering statistics material. Similar results on females' negative attitudes have been discussed [11] but others have reported no differences between males and females [10], [12]. The results of another study [8] revealed that further attention may be required to improving female attitudes toward statistics particularly if their academic performance also suffers.

3 Methods and Assessment

The study was conducted on two profiles of participants – government officers attending a compulsory course in statistics and data analysis as part of the requirement for securing a scholarship for further studies and postgraduate students attending a statistics and data analysis course as part of the postgraduate studies requirement. Using simple random sampling, a sample of 200 out of 240 course participants responded to the questionnaire which addresses several issues. The respondents were asked to answer a number of questions which included background and demographic information, personal characteristics, course evaluation and more importantly their perceived attitudes toward statistics (ATS) constructs across four dimensions – Affect, Cognitive Competence, Value and Difficulty. The ATS constructs were used in the study. The ATS is a 28-item instrument with a 7-point, Likert-type response format, with higher ratings indicating more positive attitudes after recoding the 19 negatively keyed items. The instrument incorporates four subscales, including the 6-item Affect subscale, the 6-item Cognitive Competence subscale, the 9-item Value subscale, and the 7-item Difficulty subscale. Examples of items/constructs on the Affect subscale are “I like statistics” and “I feel insecure when I have to do statistics problems”; on the Cognitive Competence subscale – “I make a lot of math errors in statistics” and “I can learn statistics”; on the Value subscale – “Statistics is worthless” and “I use statistics in my everyday life”; and on the Difficulty subscale – “Statistics is a complicated subject” and “Learning statistics requires a great deal of discipline” [1].

3 Classification of Discriminant Function

Discriminant function is used to examine the extent to which multiple predictor variables are related to a categorical criterion, that is, group membership. This technique is particularly useful in assessing which of a number of continuous variables best differentiates groups of individuals or in predicting group membership on the basis of discriminant function.

Discriminant function takes the following analogous form, as in (1):

$$D_1(X) = a + b_1X_1 + b_2X_2 + b_3X_3 + \ldots b_pX_p \qquad (1)$$

where D is the categorical variable to be predicted, i.e., the group membership.

Classification is based on the concepts of the discriminant score and the group centroid. The group centroid is calculated by applying the discriminant weights to the group means on each variable, as in (2).

$$\overline{D}_A = b_1\overline{X}_{1A} + b_2\overline{X}_{2A} + \ldots\ldots b_p\overline{X}_{PA} \qquad (2)$$

The discriminant function yielded is that which maximizes the difference between group centroids and minimizes overlap between the distributions of scores for the groups. If a discriminant function analysis is effective for a set of data, the classification table of correct and incorrect estimates will yield a high percentage correct. Discriminant analysis can be illustrated through a classification involving two target categories and predictor variables.

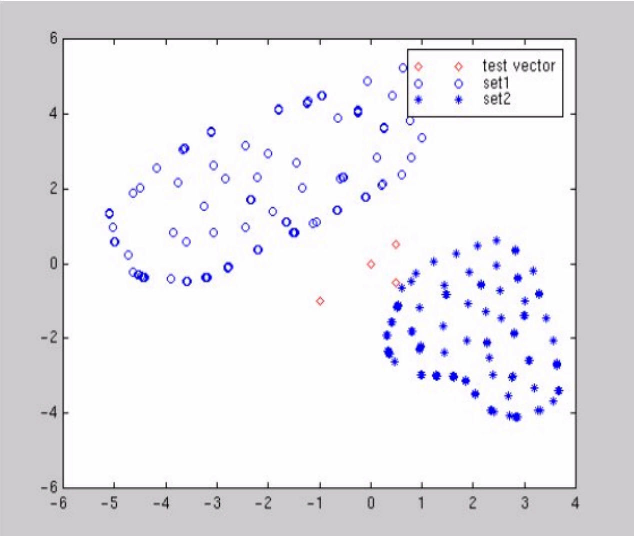

Fig. 1 Two categories with two predictors on orthogonal axes

A visual inspection in Fig. 1 shows that category 1 objects (open circles) tend to have larger values of the predictor on the Y axis and smaller values on the X axis. However, there is overlap between the target categories on both axes, hence accurate classification using only one of the predictors cannot be performed. [13]. Linear discriminant analysis finds a linear transformation ("discriminant function") of the two predictors, X and Y, that yields a new set of transformed values that provides a more accurate discrimination than either predictor alone:

Transformed Target = C1*X + C2*Y

This is illustrated in Fig. 2. A transformation function is found that maximizes the ratio of between-class variance to within-class variance as illustrated in Fig. 3. The transformation seeks to rotate the axes so that when the categories are projected on the new axes, the differences between the groups are maximized [14].

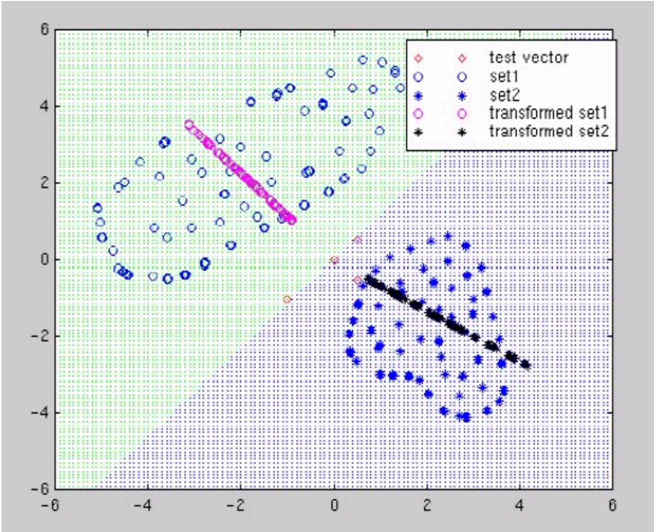

Fig. 2 Partitioning based on transformation function

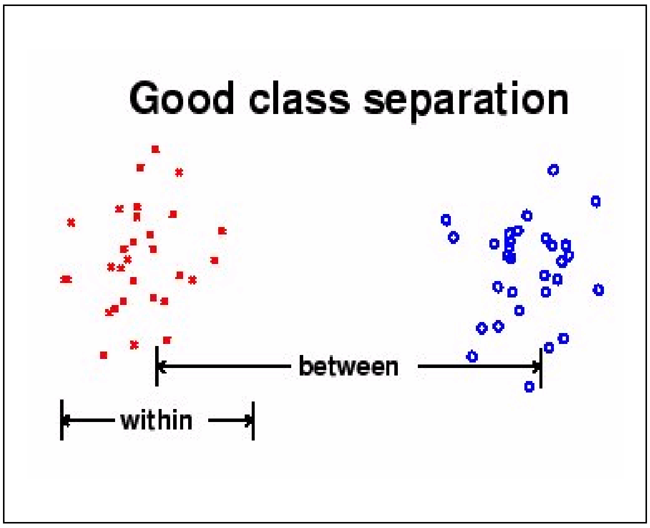

Fig. 3 Ratio of between-class variance to within-class variance

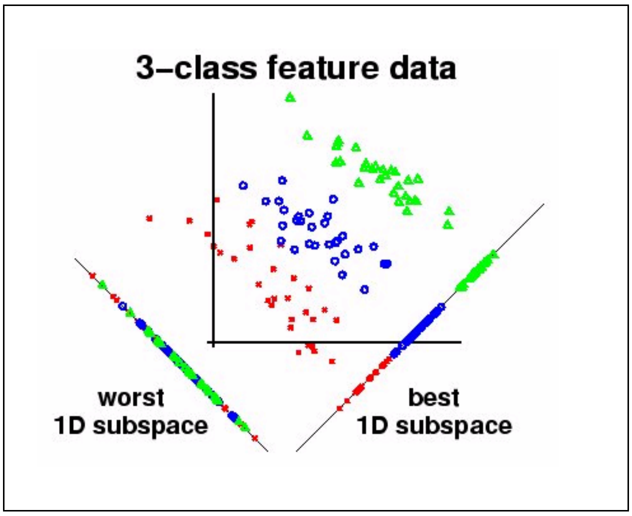

Fig. 4 Three-class feature separation

Fig. 4 shows that the projection to the lower right axis achieves the maximum separation between the categories whilst projection to the lower left axis yields the worst separation. On the other hand, Fig. 5 illustrates a distribution projected on a transformed axis. Note that the projected values produce complete separation on the transformed axis, whereas there is overlap on both the original X and Y axes.

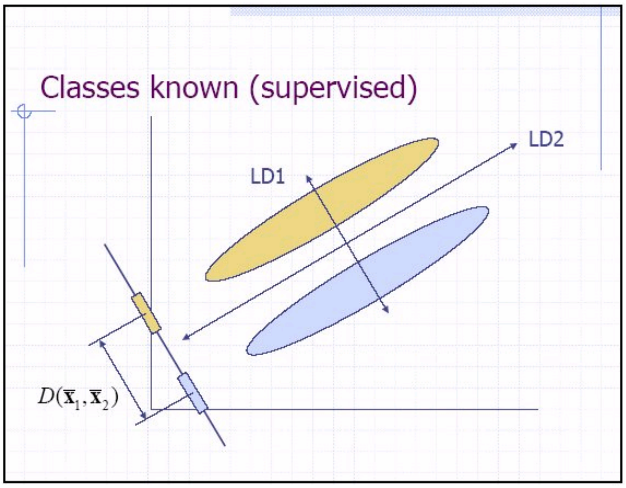

Fig. 5 Complete separation on transformed axis

In the ideal case, a projection can be found that completely separates the categories. However, in most cases there is no transformation that provides complete separation, so the goal is to find the transformation that minimizes the overlap of the transformed distributions [15]. Fig. 6 illustrates a distribution of two categories where the black line shows the optimal axis found by linear discriminant analysis that maximizes the separation between the groups when they are projected on the line.

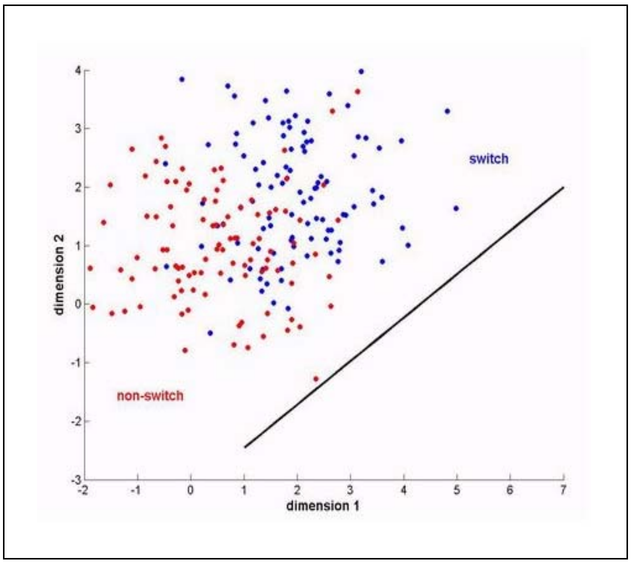

Fig. 6 Distribution of two categories

Fig. 7 further shows the distribution of the switch and non-switch categories as projected on the transformed axis (i.e., the black line shown in Fig. 6 above). Note that even after the transformation there is overlap between the categories, but setting a cutoff point around -1.7 on the transformed axis yields a reasonable classification of the categories [16].

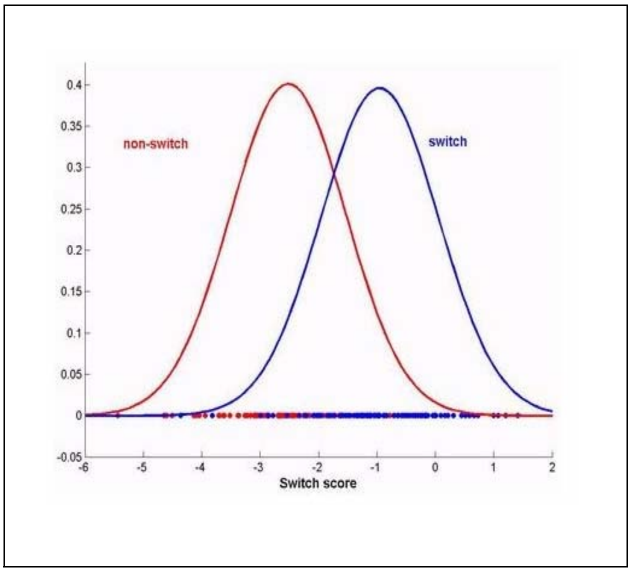

Fig. 7 Distribution of switch and non-switch categories

4.1 Two-group discriminant function

Also known as Fisher linear discriminant analysis [17], [18], the two-group discriminant analysis fit a linear equation of the type:

$$D_1(x) = a + b_1x_1 + b_2x_2 + \dots + b_px_p$$

Where a is a constant and $b_1, b_2, \dots, b_p$ are regression coefficients. The larger the standardized coefficient β (also known as canonical function) the greater is the contribution of the respective variable to the discrimination between groups. The nature of the discrimination for each discriminant function can be identified by looking at the means for the functions across groups. Visualization of how the two functions discriminate between groups are shown in the previous section.

4.2 Factor Structure Matrix

Factor structure matrix determines which variables mark or define a particular discriminant function. Several researchers have argued that these structure coefficients should be used when interpreting meaning of discriminant function. The reasons given are that (1) supposedly the structure coefficients are more stable, and (2) they allow for the interpretation of factors (discriminant functions) in the manner that is analogous to factor analysis [19]. However, subsequent Monte Carlo research has shown that the discriminant function coefficients and the structure coefficients are about equally unstable, unless the n is fairly large. Discriminant function coefficients denote the unique (partial) contribution of each variable to the discriminant function(s) [20], [21], [22].

5 Analysis and Results

This study uses discriminant analysis, a method used to assess whether or not a set of variables discriminates between two groups of participants. Discriminant analysis produces discriminant function coefficients for each predicting variable, which indicates the importance of each variable. This study also uses means to compare the differences in the perceived attitudes of learners between the profile and characteristics of the participants. Learners' attitudes toward statistics were investigated in order to identify the categories of attitude - positive and negative based on their perceived attitudes toward statistics across the four dimensions namely, Affect, Cognitive Competence, Value, and Difficulty. Based on the variable distribution (ranging from 1 to 7), positive attitude was determined as equal to or greater than 4.50 and negative attitudes was set as equal to or smaller than 3.50. Consequently, 163 respondents (82% of the total number of respondents) were included in the analysis with 133 (81.6%) learners having positive attitude and 30 (18.5%) learners displaying negative attitudes toward statistics. The rest, 37 respondents (18.5%) were in the mid-range of the scale, where attitudes were considered to be neither positive nor negative. Of the learners with positive attitudes, 79% were government officers, 21% were postgraduate research students; 48% were males, and 52% were females; of the learners with negative attitudes. 50% were government officers and 50% were postgraduate students. About 57% were males, and 43% were females. Both groups attended the statistics and data analysis course conducted at different point of time.

In the following stage, statistical differences were tested between learners with positive and negative attitudes in relation to the predictors. Table 1 depicts the results for the test for equality of group means. Based on these tests, it was determined which of the variables discriminated between learners with positive and negative attitudes. The variables that showed differences between positive and negative learners were types of learners, mode of study, perceived attitudes toward statistics based on the Affect, Cognitive Competence, Value and Difficulty subscales, mode of study and learners' evaluation towards the statistics course. Gender was excluded since there was no significant difference. Finally, a discriminant analysis was conducted to predict group membership from a set of the statistically significant predictors. Table 2 presents the results of the discriminant analysis model. It shows that the variable with the largest effect on attitudes is course evaluation followed by mode of study, value, types of learners, cognitive competence, affect and difficulty. Box's M test result in Table 3 indicates that the data do not differ significantly from the multivariate normal (p =.168).

Discriminant analysis maximizes the between-groups differences on discriminant scores and minimizes the within-groups differences. The eigenvalue is one statistics for evaluating the magnitude of a discriminant analysis. In Table 3, the eigenvalue was 5.913 with a canonical correlation of 0.925. Squaring the canonical function equals 0.855 which indicates that 85.6% of the variability of the scores for the discriminant funtion is accounted for by the differences between the two groups of learners. Here the eigenvalue is high which implies that the between-groups differences are much greater than the within-group differences. Wilks' λ indicates how good the discriminating power of the model is. Wilk's λ, which equals 0.145, indicate that differences between the two groups of learners account for 100% of the variance in predicting the variables. The significance of the χ^2 implies that the discriminant functions discriminate learners with positive and negative attitudes toward statistics well. The discriminant analysis also reveals that for both positive and negative learners, 100% of the original cases are correctly classified.

The differences between learners with positive and negative attitudes toward statistics with regard to the predicting variables that were found to be statistically significant are also described in Table 4. The results revealed two different profiles of learners with positive and negative attitudes toward statistics where learners who were classified as having positive attitudes were government officers enrolled in a full time masters by course of study and learners who were classified as having negative attitudes were comparable between postgraduates and government officers, also enrolled in a full-time masters by course of study. There is no significant difference of attitudes between the male and female respondents.

This result is consistent with the findings as in [10],[12]. In Table 6, all ATS dimensions (Value, Cognitive Competence, Affect, Difficulty) were significantly different between the two profiles of learners. Fig. 8 to Fig. 11 show that respondents with positive attitude scored higher in the median, minimum and maximum values of the ATS subscales compared to those with negative attitudes. Those with a positive attitude towards statistics perceived him/herself as liking statistics; feeling secure in doing statistics problems; competent in statistical thinking and computation; that statistics is useful in his/her daily and professional life and that statistics is not a complicated subject to learn.

Table 1 Tests of equality of group mean

Predictor variables	Wilks' Lambda	F	df1	df2	Sig.
Types of Learners	.948	8.658	1	158	.004
Gender	.998	.312	1	158	.577
Age	.991	1.490	1	158	.224
Mode of Study	.974	4.230	1	158	.041
Program Structure	1.000	.031	1	158	.860
Affect	.713	63.619	1	158	.000
Cognitive Competence	.741	55.284	1	158	.000
Value	.740	55.594	1	158	.000
Difficulty	.739	55.684	1	158	.000
Course Evaluation	.219	564.729	1	158	.000

Table 2 Discriminant analysis of learners'attitudes toward statistics

Predictor Variables	Canonical Discriminant Function
Types of Learner	0.698
Mode of Study	0.973
Affect	0.512
Cognitive Competence	0.523
Value	0.900
Difficulty	0.442
Course evaluation	-3.698
Constant	3.111

Table 3 Eigenvalues and Wilks' Lambda Test

Function	Eigenvalue	% of Variance	Cum %	Canonical Correlation
1	5.913(a)	100.0	100.0	.925

Wilks' Lambda	χ^2	df	p
.145	294.837	11	.000

Table 4 Demographic variables by learners' attitudes toward statistics

Predictor	Categories	Positive (%)	Negative (%)	χ^2	p-value
Types of learners	Postgraduate students	21.1	50.0	10.562	.001**
	Government officers	78.9	50.0		
Mode of study	Full time	91.7	78.6	4.172	.041*
	Part time	8.3	21.4		
Program Structure	PhD	37.6	33.3	8.176	.017*
	Masters by research	8.3	26.7		
	Masters by coursework	54.1	40.0		
Gender	Male	56.7	48.1	0.715	.398
	Female	4303	51.9		

*p<0.05; **p<0.01

Table 5 gives some information about the group membership for each subject, probability of group membership, and discriminant scores. The asterisks identify cases that were misclassified. From the casewise diagnostic, only 9.8% was incorrectly specified as having positive attitude towards statistics instead of negative. This indicates that the membership prediction is quite good.

Table 5 Extract of Casewise Diagnostic

Casewise Statistics

	Case Number	Actual Group	Highest Group					Discriminant Scores
			Predicted Group	P(D>d | G=g)		P(G=g | D=d)	Squared Mahalanobis Distance to Centroid	Function 1
				p	df			
Original	1	2	1**	.508	1	.823	.438	-1.429
	2	2	2	.497	1	.816	.461	-.236
	3	2	2	.270	1	.602	1.218	-.660
	4	2	1**	.948	1	.955	.004	-2.027
	5	1	1	.527	1	.833	.399	-1.459
	6	2	2	.646	1	.988	.212	.904
	7	2	2	.467	1	.797	.530	-.284
	8	1	1	.576	1	.990	.313	-2.650
	9	1	1	.021	1	1.000	5.354	-4.405
	10	1	1	.088	1	.999	2.913	-3.798
	11	2	2	.059	1	1.000	3.560	2.330
	12	1	1	.705	1	.985	.143	-2.469
	13	1	1	.449	1	.994	.572	-2.848
	14	1	1	.647	1	.886	.210	-1.633
	15	2	2	.260	1	.588	1.269	-.683
	16	2	1**	.227	1	.538	1.459	-.883
	17	2	2	.454	1	.789	.560	-.304
	18	2	2	.415	1	.759	.664	-.371
	19	2	2	.426	1	.768	.633	-.352
	20	2	1**	.344	1	.693	.896	-1.144
	21	2	2	.516	1	.827	.422	-.206
	22	2	2	.730	1	.983	.119	.788
	23	1	1	.756	1	.982	.097	-2.402
	24	2	2	.281	1	.997	1.163	1.522
	25	2	2	.277	1	.612	1.182	-.644
	26	1	1	.239	1	.998	1.385	-3.268
	27	1	1	.243	1	.998	1.362	-3.258

Table 6 Mean ATS and course evaluation by learners' attitudes toward statistics

Dimensions of ATS	Reliability[a]	Positive Mean (SD)	Negative Mean (SD)	t-statistics	p-value
Value	0.807	5.45 (.70)	4.36 (.69)	7.727	.000**
Cognitive Competence	0.805	5.18 (.66)	4.01 (.85)	8.290	.000**
Affect	0.800	5.17 (.83)	3.81 (.63)	8.414	.000**
Difficulty	0.697	3.76 (.74)	2.64 (.49)	10.143	.000**
Course Evaluation	0.749	5.41 (.537)	2.90 (.305)	24.637	.000**

[a]Cronbach's α.
*p<0.05; **p<0.01

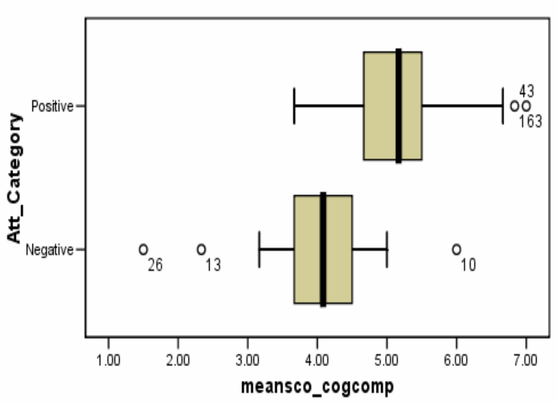

Fig. 8 Profile of learners' attitudes toward statistics (Cognitive competence subscale)

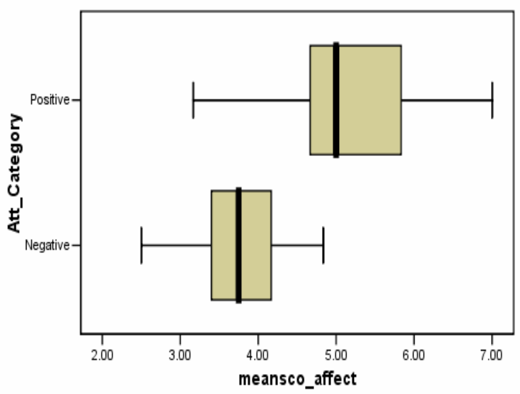

Fig. 9 Profile of learners' attitudes toward statistics (Affect subscale)

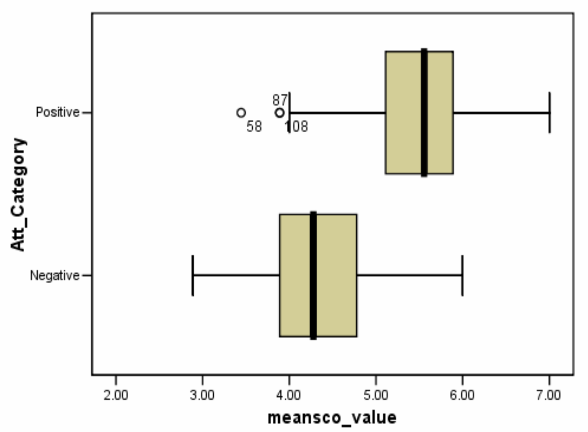

Fig. 10 Profile of learners' attitudes toward statistics (Value subscale)

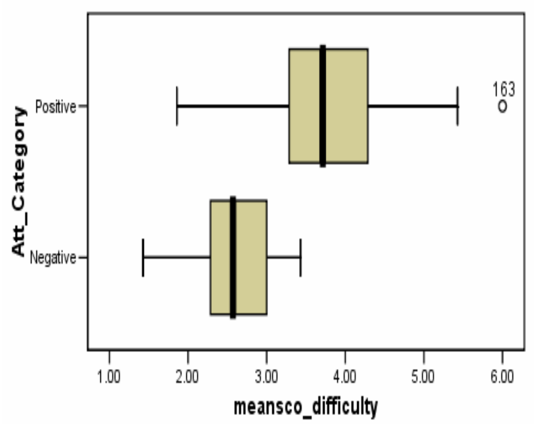

Fig. 11 Profile of learners' attitudes toward statistics (Difficulty subscale)

4.1 Attitudes Toward Statistics

Scores from the ATS assessed four components of Attitudes Toward Statistics. These components include the following:

i. Affect (six items): Students' positive and negative feelings about statistics
ii. Cognitive Competence (six items): Attitudes about the students' intellectual knowledge and skills when applied to statistics
iii. Value (nine items): Attitudes about the usefulness, relevance, and worth of statistics in personal and professional life
iv. Difficulty (seven items): Attitudes about the difficulty of statistics as a domain

Results of the assessment of students' positive and negative feelings about statistics show that 78% of the respondents enjoyed taking statistics and 71% were not under stress during statistics class On average, 60% had a positive attitude toward statistics in the Affect component (see Table 7).

Table 7 Attitudes Toward Statistics based on Affect items

No.	Attitudes Towards Statistics (AFFECT items)	Agree (%)	Neutral (%)	Disagree (%)
1	I like statistics	60.5	27.9	11.6
2	I feel secure when I have to do statistics problems	32.6	18.6	48.8
11	I do not get frustrated going over statistics problem exercises in class	64.3	23.8	11.9
14	I am not under stress during statistics class	71.4	19.1	9.5
15	I enjoy taking statistics course	78.0	14.0	7.3
21	I am not scared by statistics	54.8	19.0	26.2
	Mean/Median (%) Affect	60.3		11.8

In the assessment of attitudes about the students' intellectual knowledge and skills when applied to statistics - Cognitive Competence, a majority said that they could learn statistics. Slightly over 70% said that they had some idea of what was going on in statistics and that they could understand statistics equation. On average, 66% had a positive attitude towards statistics in the Cognitive Competence component (see Table 8).

Table 8 Attitudes toward statistics based on *Cognitive Competence* items

No.	Attitude Towards Statistics (COGNITIVE COMPETENCE items)	Agree (%)	Neutral (%)	Disagree (%)
3	I do not have trouble understanding statistics because of how I think	48.8	23.3	27.9
9	I have some idea of what's going on in statistics	73.8	11.9	14.3
20	I do not make a lot of math errors in statistics	45.2	35.7	19.1
23	I can learn statistics	92.9	7.1	-
24	I understand statistics equations	78.6	11.9	9.5
27	I find it easy to understand statistics concepts	54.8	14.3	31.0
	Mean/Median (%) Cognitive Competence	65.7		16.9

In the assessment of attitudes about the usefulness, relevance, and worth of statistics in personal and professional life, results show that a majority felt that statistics should be a required part of their professional training and that it was useful and applicable outside their jobs. On average, 72% had a positive attitude towards statistics in the Value component (see Table 9).

Table 9 Attitudes toward statistics based on *Value* items

No.	Attitude Towards Statistics (VALUE items)	Agree (%)	Neutral (%)	Disagree (%)
5	Statistics is useful	76.2	11.9	11.9
7	Statistics should be a required part of my professional training	88.4	9.3	2.3
8	Statistical skills will make me more employable	79.1	16.3	4.7
10	Statistics is useful to the typical professional	78.6	7.1	14.3
12	Statistical thinking is applicable in my life outside my job	81.0	4.8	14.2
13	I use statistics in my everyday life	45.2	21.5	33.3
16	Statistics conclusion are often presented in everyday life	50.0	2.4	47.6
19	I will have some application for statistics in my profession	82.9	9.8	7.3
25	Statistics is relevant in my life	69.0	23.8	7.1
	Mean/Median (%) Value	72.3	11.9	15.9

Table 10 Attitudes toward statistics based on *Difficulty* items

No.	Attitudes Towards Statistics (DIFFICULTY items)	Agree (%)	Neutral (%)	Disagree (%)
4	Statistics formulas are easy to understand	42.9	19.0	38.1
6	Statistics is not a complicated subject	39.5	18.6	41.9
17	Statistics is a subject quickly learned by most people	23.8	26.2	50.0
18	Learning statistics do not require a great deal discipline	4.8	11.9	83.3
22	Statistics do not involve massive computations	28.6	19.0	52.4
26	Statistics is not highly technical	23.8	26.2	50.0
28	Most people do not have to learn a new way of thinking to do statistics	11.9	33.3	54.8
	Mean/Median (%) Difficulty	25.0		50.0

across ATS dimensions

With respect to attitudes about the difficulty of statistics as a domain, a majority felt that learning statistics required a great deal of discipline. On average, 50% of the respondents perceived some difficulties in learning statistics (see Table 10).

Among the ATS components, the median percentage attitude about the students' intellectual knowledge and skills when applied to statistics was highest. On the other hand, the lowest median percentage attitude was found with those who agreed less on the usefulness, relevance, and worth of statistics in personal and professional life. The median percentage attitude about the difficulty of statistics as a domain was found to be the highest (see Fig.12). This indicates that the majority of respondents disagreed that statistics was an easy subject to handle.

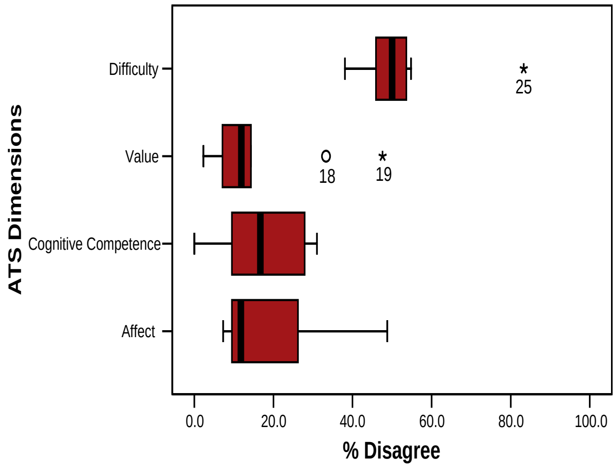

Fig.12 Distribution of responses across ATS dimensions

The average mean scores of female respondents across all ATS components is higher than the male respondents. The female group indicates a strong agreement towards all items in three components (Affect, Cognitive Competence and Value) with the exception of Difficulty component which indicates a moderate to low agreement towards its items (see Table 11). The average mean score of items across all ATS components is comparable among each other. There was no significant difference in the average mean score items across all ATS components.

Table 11 Comparison of ATS scores between gender group

	Gender	N	Mean	Std. Deviation	Std. Error Mean
Mean score Affect	Male	18	4.4907	1.01214	.23856
	Female	25	5.0280	.99404	.19881
Mean score Cognitive Competence	Male	18	4.6574	1.17639	.27728
	Female	25	5.1200	.87734	.17547
Mean score Value	Male	18	4.8210	.96725	.22798
	Female	25	5.4678	.84503	.16901
Mean score Difficulty	Male	18	3.2698	.77922	.18366
	Female	25	3.6457	.96196	.19239

6 Discussion and Implications

Based on the canonical discriminant equation of *D = 3.111-3.698(course evaluation) + 0.973 (mode of study) + 0.900(value) + 0.698(type of learner) + 0.523 (cognitive competence) + 0.512 (affect) + 0.442 (difficulty)*, future predictions can be made on the profile of learners' with regard to their attitudes toward statistics. The study reveals two profiles of statistics learners, one group with a positive attitude towards statistics, and another group with negative attitudes toward statistics. The groups can be distinguished by learners' perceived attitudes toward statistics across the four ATS dimensions (Value, Cognitive Competence, Affect, Difficulty), mode of study, types of learner, program structure and course evaluation.

The findings have important implications for both learners and instructors of statistics. Even though the percentage of those with negative attitudes is small, instructors must be aware of the effect of their methods and approach of teaching statistics on learners' attitudes toward statistics. Instructors should therefore be attentive to the various components of teaching methodology and the effective delivery of statistics contents rather than just focusing on rote learning. Learners who evaluate high on the course tend to perceive their attitudes toward statistics positively than those who evaluate low on the course. Those who enroll in full time programs also tend to perceive their attitudes toward statistics positively than those who enroll in the part time programs. This should also be of concern to instructors, as different approaches may need to be adopted in handling between full-time and part-time learners. Based on the scores of each ATS dimensions, learners who scored high on the Value, Cognitive Competence, Affect and Difficulty subscales tend to perceive their attitudes toward statistics positively.

In this study, the discriminant function analysis prediction will help course instructors to distinguish the group of learners and identify factors that predict learners' attitudes toward statistics. Knowing the profile of learners would enable instructors' to diversify their course contents and develop more innovative methods of teaching statistics. Perhaps a more practical and worked example approach plus remedial classes provided for learners with negative attitudes toward statistics can encourage active participation in the classroom and spark more interest in learning statistics.

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