# PARTIAL LEAST SQUARES MODELLING OF ATTITUDES OF STUDENTS TOWARDS LEARNING STATISTICS

(Pemodelan Kuasa Dua Terkecil Separa Sikap Pelajar Terhadap Pembelajaran Statistik)

# HASSAN RAHNAWARD GHULAMI, MOHD RASHID AB HAMID & ROSLINAZAIRIMAH ZAKARIA

#### ABSTRACT

Attitudes of students are vital in determining the perceived achievements in statistics subject. Therefore, this study investigates the relationship of attitudes of students towards learning statistics using several constructs which are affect, cognitive, value, difficulty, interest, effort and perceived achievement in statistics subject. Structural Equation Modelling – Partial Least Squares methodology was used to assess the hypothesised model that linked all the constructs of attitudes of students with the perceived achievement. The questionnaire was adopted from previous study and distributed to undergraduate students at Universiti Malaysia Pahang. From the analysis, it reveals that all the relationships in the hypothesised model were significant at p < 0.05 and this shows that all constructs of attitudes of students play a vital role in learning statistics. In short, this study reinforces the understanding of students' attitude and could be a step forward for the lecturer to arouse the students' interest in the teaching and learning process particularly for statistics.

Keywords: attitudes; education; statistics; learning

#### ABSTRAK

Sikap pelajar adalah penting dalam menentukan tanggapan terhadap pencapaian dalam subjek statistik. Oleh itu, kajian ini mengkaji hubungan sikap pelajar terhadap pembelajaran statistik menggunakan beberapa konstruk, iaitu afek, kognitif, nilai, kesukaran, minat, usaha dan pencapaian yang diidamkan dalam subjek statistik. Pemodelan Persamaan Struktur – Kuasa Dua Terkecil Separa digunakan untuk menilai model hipotesis yang menghubungkan kesemua konstruk sikap pelajar dengan pencapaian yang diidamkan. Soal selidik telah diadaptasi daripada kajian sebelumnya dan diedarkan kepada pelajar sarjana muda di Universiti Malaysia Pahang. Daripada analisis, didapati bahawa semua hubungan dalam model hipotesis adalah signifikan pada p < 0.05 dan ini menunjukkan bahawa semua konstruk sikap pelajar memainkan peranan penting dalam pembelajaran statistik. Pendek kata, kajian ini menguatkan pemahaman terhadap sikap pelajar dan boleh menjadi titik tolak kepada pensyarah untuk membangkitkan minat pelajar dalam proses pengajaran dan pembelajaran khususnya untuk statistik.

Kata kunci: sikap; pendidikan; statistik; pembelajaran

#### 1. Introduction

Most university students often experience anxiety and have negative attitudes towards learning mathematics especially statistics. These feelings are frequently considered as a major obstacle for successful learning (Onwuegbuzie & Wilson 2003). It has been reported that attitudes of students towards statistics are related to ability in mathematics and might play an effective role in perception on statistics achievement and statistical performance because learners expect that learning statistics involves strong mathematical knowledge (Dempster & McCorry 2009; Emmoglu 2011). In the context of statistics education, the attitudes towards statistics is an important concept and should be taken note of (Vanhoof 2010). Attitudes towards statistics has been defined as a "multidimensional concept referring to distinct but related dispositions

pertaining to favourable or unfavourable responses with regards to statistics and statistics learning" (Vanhoof 2010). It has also been stated that the attitudes of students towards statistics may affect the learning process outside the classroom (Schau 2003a).

Positive attitude is a dynamic trait that could encourage student to become more engaged in the learning process (Ashaari *et al.* 2011). Based on the study by Griffith *et al.* (2012), it was found that the responses from students with a positive attitude can be categorised into five, which are (1) use in future career, (2) necessary for graduate school, (3) to become Professor, (4) like mathematics, and (5) challenging course. It is noted that attitudes of students and perception on statistics have a noticeable impacts on the teaching and learning process and thus require substantial attention (Ashaari *et al.* 2011). In this study, attitudes of students towards statistics are investigated based on their perceived attitude towards statistics that include Affect, Cognitive Competence, Value, Difficulty, Interest and Effort (Schau 2003a). A hypothesised model for attitudes of students towards statistical learning has been proposed and evaluated.

#### 2. Literature Review

The Affect factor is a means of gauging the students' positive or negative feelings on statistics learning (Schau 2003a), which can be used to capture the attitudes on statistics that may have resulted from prior experiences or feedbacks from others (Larwin 2007). Affect construct is an endogenous variable in this study that can be predicted by Cognitive Competence. It has been stated that there is a strong, statistically significant and positive correlation between the variables of Affect and Cognitive Competence (Emmoglu 2011), and the findings are also shared by other researchers (Nolan *et al.* 2012). Therefore, the first hypothesis tested is:

#### H1: There is positive relationship for Cognitive Competence on Affect.

The second construct in this model is Cognitive Competence, which can be used to measure attitudes of students about intellectual knowledge and skills towards statistics learning (Schau 2003a). The learners' attitudes, which is related to the learners' perceived capacity for success, can be understood by observing the variable of Cognitive Competence (Larwin 2007). The cognitive ability is an endogenous variable in this study which can be predicted by Difficulty. Thus, the second hypothesis to be tested is:

## H2: There is positive relationship for Difficulty on Cognitive Competence.

The third construct of this model is Value, which is used to measure the attitudes of students regarding the usefulness, relevance and worth of statistics in personal and professional life (Schau 2003a). The indicators of Value are related to the Expectancy-value theory, in which the students are more motivated to work on a task if a successful outcome is more worthwhile or valued to him (Larwin 2007). The Value construct is an endogenous variable in this study since it is proposed to be predicted by Interest. Thus, the third hypothesis to be tested is:

### H3: There is positive relationship for Interest on Value.

The fourth construct of this model is Difficulty, which is used to measure attitudes of students on the difficulty of statistics as a subject (Schau 2003a). The indicators of Difficulty attempt to conclude if the learner perceives statistics as a difficult subject, as well as assess the

student's outcome expectancy for the class, one of which is class material that may be out of the students' skill to control (Larwin 2007).

The fifth construct of this model is Interest, which is used to measure the learners' level of individual interest about the subject of statistics (Schau & Emmoglu 2011). The construct of Interest is an endogenous variable that could be predicted by Cognitive Competence, Difficulty, and Affect variables. Some researchers have proven that correlation between Interest and Affect, Cognitive Competence and Difficulty are high (Vanhoof *et al.* 2011), while others have proposed that the relationship between the variables of Interest and Affect, Cognitive Competence, significant and positively correlated (Emmoglu 2011). Hence, for these reasons, the following hypotheses are tested:

- H4: There is positive relationship for Affect on Interest.
- H5: There is positive relationship for Cognitive Competence on Interest.
- H6: There is positive relationship for Difficulty on Interest.

The sixth construct of this model is Effort, which measures the learners' amount of time that they spend to learn statistics (Schau & Emmoglu 2011). Also, the Effort construct is an endogenous variable since it is proposed to be predicted by Interest variable. It has been stated that the relationship between the Effort and Interest variable is moderate, statistically significant and positively correlated (Emmoglu 2011), and similarly, it has been shown that correlation between Effort and Interest are statistically significant and positively correlated. (Tempelaar *et al.* 2007). Thus, this leads to the following hypotheses:

#### H7: There is positive relationship for Interest on Effort.

The last construct is Statistics Achievement, which is used to measure the perceptions of success in statistics, perceptions of outcomes from prior learning experiences towards statistics, and expectation of students about the grade earned from statistics courses (Sorge & Schau 2002). Findings from several studies have shown a positive relationship between Statistics Achievement and each attitude constructs. It has been reported that there is a high and statistically significant correlation between Statistics Achievement and constructs of attitudes such as Affect, Cognitive Competence and Difficulty, and Value (Emmoglu *et al.* 2012), while other studies have found that the relationship is positive, statistically significant, and moderately correlated (Sorge 2001). Thus, this leads to the following hypothesis:

H8: There is positive relationship for Interest on Statistics Achievement.H9: There is positive relationship for Value on Statistics Achievement.H10: There is positive relationship for Effort on Statistics Achievement.

Therefore, based on the justifications mentioned, the conceptual framework that depicts the relationships among the constructs as hypothesised is shown in Figure 1.

## 3. Methodology

The data are collected during the first semester of the academic year, between November 18-27, 2013, from 783 undergraduate engineering students who were enrolled in applied statistics course from the different faculties at Universiti Malaysia Pahang (UMP). Students were required to fill up all demographic details as indicated in the questionnaire before answering all the items.

# 3.1. Questionnaire

The instrument used in this study to collect data was adopted from the Survey of Attitudes Towards Statistics (SATS) (Schau 2003b). It was used as it is the most current instrument developed to assess attitudes and achievements towards statistics (Emmoglu 2011). Secondly, the psychometric properties of the instrument are well-documented and supported by confirmatory analysis techniques (Chiesi *et al.* 2009). Thirdly, the generation of the subscales was based on a theoretical background (Schau 2003a). And finally, the instrument is adaptable to different cultures as it has been used across different cultural contexts (Dauphinee *et al.* 1997; Dempster & McCorry 2009; Emmoglu 2011; Estrada *et al.* 2005; Nasser 2004; Schau 2003a; Schutz *et al.* 1998; Sorge & Schau 2002; Tempelaar *et al.* 2007; Bond *et al.* 2012; Chiesi & Primi 2010).

As discussed earlier, the hypothesised model of attitudes of students towards statistics consist of seven latent constructs. The first construct is Affect that represents students' positive and negative feeling towards statistics learning, where six items Af1 - Af6 were coded. The second construct is cognitive ability that represents the students perception about intellectual knowledge and skills (Schau & Emmoglu 2011), where seven items CC1 - CC7 were coded. The third construct is Interest of statistics that assesses students' level of individual interest in statistics (Schau & Emmoglu 2011), where five items I1 - I5 were coded. Value construct is the fourth attitude construct that assesses attitudes of students towards the usefulness, relevance and advantage of statistics for individuals and their professional life (Schau & Emmoglu 2011), where nine items V1 - V9 were coded. Effort is the fifth attitude construct that measures the amount of time that students spends to learn statistics (Schau & Emmoglu 2011), where four items E1-E4 were coded. While Statistics Achievement assesses students' perception of the applicability of statistics, confidence about the use of statistics, and expectation of students about the grade earned from statistics courses (Sorge & Schau 2002), where six items SA1-SA6 were coded. Lastly, Difficulty is the exogenous construct that measures the attitudes of students towards the difficulties in understanding of statistics (Schau & Emmoglu 2011), where seven items D1-D7 were coded. All the items are shown in Table 1.

Constructs	Labels	Indicators
Affect	Af_1	I like learning about statistics
	Af_2	I feel insecure when I have to solve statistics problems
	Af_3	I get frustrated with my statistics tests results
	Af_4	I am under stress during statistics class
	Af_5	I enjoy taking statistics courses
	Af_6	I am scared by statistics
Cognitive	CC_1	I have trouble understanding statistics because of the way I think
Competence	CC_2	I have no idea of what is going on in this statistics course
	CC_3	I make a lot of mathematical errors in statistics
	CC_4	I can understand most of the statistical ideas
	CC_5	I understand equations related to statistics
	CC_6	I find it difficult to understand statistical concepts
Value	V_1	Statistics is not useful in my daily routine
	V_2	Statistics is required in my professional training
	V_3	Statistical skills will make me more employable
	V_4	Statistics is not useful at the workplace
	V_5	Statistical thinking is not applicable outside my career/profession
	V_6	Use statistics in my everyday life
	V_7	Statistics knowledge are rarely applied in daily life
	V_8	I have no application for statistics in my future profession
	V_9	Statistics is irrelevant in my life
Difficulty	D_1	Statistics formulas are easy to understand
	D_2	Statistics is a complicated subject
	D_3	Statistics is a subject quickly learned by most people
	D_4	Learning statistics requires a great deal of discipline
	D_5	Statistics involves massive computations
	D_6	Statistics involves massive computations
	D_7	Most people have to learn a new way of thinking to do statistics
Interest	I_1	I am interested in being able to communicate statistical information to others
	I_2	I am interested in using statistics
	I_3	I am interested in understanding statistical information
	I_4	I am interested in learning statistics
	I_5	I like learning statistics by using the software like Microsoft Excel, SPSS, etc
Effort	E_1	I plan to complete all of my statistics assignments
	E_2	I plan to work hard in my statistics course
	E_3	I plan to study hard for every statistics test
	E_4	I plan to attend every statistics class session

Table 1: Questionnaire items on attitudes of students towards statistics model

# 3.2. Samples

The target population of the current study was all engineering students from eight faculties in UMP who enrolled in applied statistics course during the first semester of 2013 academic year which involved 783 samples. However, a total of 65 students did not participate in the survey

either from their own refusal or have provided incomplete data about themselves, and therefore the model was tested with 718 engineering undergraduate students with 445 males (62%) and 273 females (38%).

## 4. Data Analysis

The hypothesised model is tested using Structural Equation Model – Partial Least Squares (SEM-PLS) in Smart PLS M3 version 2.0 (Ringle *et al.* 2005).

## 4.1. Assessment of Outer Model

The relationship between the attitudes of students towards statistics as well as their achievement in statistics and the indicators were tested using Partial Least Square (PLS) method. Analysis of the measurement model (or outer model), the first step of PLS analysis, is used to determine the appropriateness of the theoretically defined construct. The measurement model is examined to ensure the survey questionnaire determines the variables that were supposed to measure, and simultaneously making sure that the instrument is reliable. In this process, three things are looked into which are factor loadings, composite reliability (CR), and average variance extracted (AVE).

## 4.1.1. Construct Validity

The construct validity of specific indicators can be assessed by examining the respective cross loadings and factor loadings, where it has been recommended that a loadings of higher than 0.50 on two or more factors is considered significant (Hair *et al.* 2011). From Table 2, it is observed that all the indicators measuring a particular construct are greater than 0.50 on those particular constructs and less than 0.50 on the other constructs, thus confirming construct validity.

Previous researchers have suggested that the cut-off value for factor loadings should exceed 0.60 (Hair *et al.* 2011; Chin *et al.* 1997). Examining the factor loadings for each items of the seven unobserved variables revealed that the 32 observed variable had factor loadings in the range of 0.625 - 0.933 and all the values are positive and greater than the recommended value.

## 4.1.2. Convergent Validity

Convergent validity is the degree to which multiple items that measure the same concept are in agreement. Factor loadings, CR and AVE can be used to assess convergent validity (Hair *et al.* 2011). Initially, there were items that were deleted in order to increase the value of CR which are two indicators from Affect (Af 2 and Af 3), two indicators (CC 3 and CC 6) from Cognitive Competence, two indicators (V\_6 and V\_7) from Value, and four indicators (D\_4, D\_5, D\_6 and D\_7) from Difficulty constructs. This procedure was conducted as suggested by Hair *et al.* (2011) which mentioned that the items with loadings between 0.40 and 0.70 should be removed from the measure if deleting the observed variable would increase the composite reliability in the reflective scales. Hence, after the deletion, all values of factor loadings, CR and AVE are greater than the recommended cutoff values, hence confirming that the measurement model has a convergent validity.

	Affect	Cog-Comp	Difficulty	Effort	Interest	Sta-Achiev	Value
Af_1	0.788	0.467	0.470	0.305	0.574	0.450	0.382
Af_4	0.716	0.493	0.408	0.199	0.324	0.218	0.268
Af_5	0.800	0.468	0.430	0.320	0.469	0.363	0.328
Af_6	0.628	0.482	0.304	0.059	0.197	0.183	0.178
CC_1	0.435	0.670	0.387	0.043	0.181	0.189	0.228
CC_2	0.567	0.765	0.405	0.220	0.329	0.279	0.358
CC_4	0.448	0.757	0.403	0.225	0.415	0.374	0.333
CC_5	0.458	0.782	0.442	0.250	0.428	0.378	0.314
D_1	0.459	0.440	0.810	0.273	0.427	0.290	0.199
D_2	0.405	0.435	0.640	0.123	0.241	0.170	0.204
D_3	0.388	0.370	0.797	0.216	0.431	0.287	0.251
E_1	0.295	0.247	0.267	0.859	0.399	0.307	0.264
E_2	0.305	0.247	0.275	0.933	0.403	0.334	0.315
E_3	0.263	0.227	0.241	0.896	0.360	0.306	0.294
E_4	0.231	0.163	0.171	0.794	0.300	0.224	0.230
I_1	0.406	0.366	0.353	0.316	0.805	0.493	0.431
I_2	0.535	0.452	0.491	0.371	0.921	0.541	0.540
I_3	0.472	0.406	0.416	0.409	0.903	0.486	0.509
I_4	0.559	0.442	0.507	0.424	0.892	0.495	0.496
I_5	0.298	0.226	0.251	0.209	0.625	0.402	0.281
SA_1	0.254	0.232	0.184	0.307	0.392	0.771	0.451
SA_2	0.295	0.323	0.225	0.265	0.461	0.844	0.541
SA_3	0.219	0.193	0.156	0.171	0.435	0.705	0.391
SA_4	0.501	0.505	0.410	0.348	0.495	0.741	0.356
SA_5	0.399	0.357	0.332	0.230	0.469	0.828	0.432
V_1	0.336	0.298	0.209	0.207	0.365	0.350	0.669
V_2	0.226	0.250	0.150	0.238	0.407	0.436	0.704
V_3	0.287	0.299	0.219	0.306	0.479	0.477	0.760
V_4	0.311	0.353	0.232	0.235	0.403	0.406	0.787
V_8	0.295	0.282	0.221	0.181	0.371	0.381	0.738
V_9	0.323	0.351	0.232	0.203	0.359	0.378	0.703

Table 2: Loadings and cross loadings

<sup>a</sup> Loadings which are above the recommended value of 0.50 are in bold.

As shown in Table 3, CR is calculated from the factor loadings of the observed variable that is accounted for by each of the specified latent constructs. From the table, all the composite reliability values obtained lie in the range of 0.795 to 0.927, which exceeded the recommended value of 0.70 and these values are reliable (Hair *et al.* 2011).

	Table 5. N		1		
Constructs	Items	Loadings	AVE <sup>a</sup>	$CR^{b}$	
Affect	Af_1	0.788	0.542	0.824	
	Af_4	0.716			
	Af_5	0.800			
	Af_6	0.628			
<b>Cognitive Competence</b>	CC_1	0.670	0.555	0.832	
	CC_2	0.765			
	CC_4	0.757			
	CC_5	0.782			
Difficulty	D_1	0.810	0.567	0.795	
	D_2	0.640			
	D_3	0.797			
Effort	E_1	0.859	0.761	0.927	
	E_2	0.933			
	E_3	0.896			
	E_4	0.794			
Interest	I_1	0.804	0.700	0.920	
	I_2	0.921			
	I_3	0.903			
	I_4	0.892			
	I_5	0.626			
Statistics Achievement	SA_1	0.770	0.608	0.885	
	SA_2	0.844			
	SA_3	0.705			
	SA_4	0.742			
	SA_5	0.828			
Value	V_1	0.665	0.530	0.887	
	V_2	0.682			
	V_3	0.739			
	V_4	0.801			
	V_5	0.761			
	V_8	0.741			
	V_9	0.699			

Table 3: Measurement Model

<sup>*a*</sup>Average variance extracted (AVE) = (summation of the square of the factor loadings)/  $\{(summation of the square of factor loadings) + (summation of the error variances)\}$ .

(summation of the square of factor rotatings) + (summation of the error variances)). <sup>b</sup>Composite reliability (CR) = (square of the summation of the factor loadings)/{(square of the summation of the factor loadings) + (square of the summation of the error variances)}.

The last measurement to be examined is the AVE that reflects the complete amount of variance in the observed variable accounted by the latent variable relative to measurement error (Ramayah *et al.* 2013). Again, from Table 3, range of AVE lies between 0.530 - 0.700 for all constructs, which is higher than the minimum recommended value of 0.50 (Barclay *et al.* 1995).

Hence, Figure 1 illustrates the results of the measurement model. The results indicate that all the seven constructs of Affect, Cognitive Competence, Value, Difficulty, Interest, Effort and Statistics Achievement are all valid measures of their respective constructs according to their parameter estimates and are statistically significant at p < 0.05.





## 4.1.3. Discriminant Validity

The next step is to test the discriminant validity that refers to "the degree to which items differentiate among constructs or measuring distinct concepts", which is conducted by calculating and investigating the associations among the measures of possibly overlapping variables (Ramayah *et al.* 2011). Hence, discriminant validity can be assessed by examining the correlations between the measures of potential overlapping constructs. The AVE for each construct should be greater than the squares of the correlation between the constructs and all other constructs (Christmas 2005). On the other hand, the hypothesised model is considered to have a good discriminant validity when the correlation among the constructs is lower than the square root of the AVE (Fornell & Larcker 1981).

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	Affect	Cog-Comp	Difficulty	Effort	Interest	SA	Value
Affect	0.736						
Cog-Comp.	0.642	0.745					
Difficulty	0.555	0.549	0.753				
Effort	0.316	0.257	0.278	0.872			
Interest	0.554	0.463	0.495	0.423	0.837		
Stat. Achieve.	0.429	0.416	0.336	0.340	0.578	0.779	
(SA)							
Value	0.406	0.424	0.283	0.310	0.540	0.555	0.728

Table 4: Discriminant Validity

Note: Diagonal represents the square root of the AVE, while the off-diagonals represent the correlations among the variables.

It is noted that from Table 4, all of the square root of AVE (values in bold, off-diagonal) are greater than the correlations in the respective columns and rows and henceforth, the measurement model demonstrated adequate discriminant validity.

## 4.2. Assessment of Inner Model

Then, the next step is the assessment of the structural model (inner model) for examining the hypothesised relationships between constructs in the Attitudes of Students-Achievement towards Statistics Model. Firstly, the weights or path coefficients of the relationships are looked into and tested for their significance through *t*-values obtained from the bootstrapping method. Also, the coefficient of determination,  $R^2$  for dependent variables are assessed in order to find the amount of variance in each construct, which are described by the model. In addition, effect size ( $f^2$ ) and predictive relevance ( $Q^2$ ) are also examined. The testing of the significance for the regression weights are achieved by running 5000 bootstrapped samples from the original 718 cases. The  $R^2$  values is presented in Table 5.

Table 5: Coefficient	of Determination
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Constructs	$R^2$
Affect (	).412
Cognitive Competence (	0.302
Effort	).179
Interest	).363
Statistics Achievement 0	).423
Value (	).292

As shown in Table 5, the  $R^2$  value for endogenous variable, Affect is 0.412, which implies that 41.2% of Affect is predicted by Cognitive Competence. Also, the  $R^2$  for Cognitive Competence is 0.302, which means that 30.2% of Cognitive Competence is explained by Difficulty. In addition, 17.9% of Effort is explained by Interest, 36.3% of the variation in Interest is explained by Affect, Cognitive Competence, and Difficulty. Furthermore, 29.2% of Value is predicted by Interest and 42.3% of statistics achievement is explained by Value, Interest and Effort. In general, the hypothesised model describes reasonably well the amount of variance explained for each endogeneous construct.

# 4.3. Hypothesis Testing

Table 6 presents the path coefficients ( $\beta$ ) and their significance values. All the relationships (path coefficients) were found to be significant. Figure 2 shows the graphical representation of the inner model with  $R^2$  coefficients. The significant paths suggested that all hypotheses were supported.

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Hypotheses	Relationships	Std. beta	SE	<i>t</i> -value	Decisions
H1	Cog-Comp> Affect	0.644	0.023	**28.486	Supported
H2	Difficulty -> Cog-Comp.	0.552	0.031	**17.732	Supported
Н3	Interest -> Value	0.541	0.031	**17.651	Supported
H4	Affect -> Interest	0.356	0.051	**6.973	Supported
Н5	Cog-Comp> Interest	0.100	0.052	*1.970	Supported
H6	Difficulty -> Interest	0.243	0.046	**5.262	Supported
H7	Interest -> Effort	0.423	0.037	**11.511	Supported
H8	Interest ->Statistics Achievement	0.363	0.039	**9.259	Supported
H9	Value -> Statistics Achievement	0.335	0.035	**9.522	Supported
H10	Effort -> Statistics Achievement	0.083	0.034	**2.451	Supported

Table 6: Hypotheses Testing

\*\*p<0.01, \*p<0.05

From this analysis, all the hypothesised relationships are supported at p < 0.01, while the relationships of Cognitive Competence on Interest is statistically significant at p < 0.05.



Figure 2: Graphical representation of inner model after the bootstrapping procedure (n = 5000 bootstrapped samples)

## 4.4. Effects Size

Effects size,  $f^2$  analysis was conducted for multiple independent variables on dependent variable, which is used to measure the changes in  $R^2$  in the attempt to understand whether or not each specific independent latent construct and dependent latent construct have a practical impact (Cohen 1988). For each of the effect through the path model, one can evaluate the effect size by means of  $f^2$  (Cohen 1988). Based on the formula for calculating  $f^2$  (Vinzi 2010), the effect size of a variable can be calculated as follows:

$$f^{2} = \frac{R^{2} \text{included} - R^{2} \text{excluded}}{1 - R^{2} \text{included}}$$

where  $R^2$  included and  $R^2$  excluded are the *R*-squares given for the dependent latent constructs when the predictor latent variable is used or omitted in the structural model, respectively.

Constructs		$R^2$ included	$R^2$ excluded	$f^2$	Conclusions
Cognitive Competence	٦		0.385	-	-
Difficulty	}	0.363	0.327	0.057	Small
Affect	J		0.301	0.097	Small
Effort	٦		0.418	0.009	None
Interest	}	0.423	-	-	-
Value	J		0.35	0.127	Small

Table 7: Effect size,  $f^2$ 

To intepret the impact of  $f^2$  at the structural level, it has been suggested that the effect is large when  $f^2$  is 0.35, medium when  $f^2$  is 0.15, and small when  $f^2$  is 0.03 (Cohen 1988). From Table 7, it indicates that Difficulty, Affect and Value have small effect on the adoption of statistics attitudes achievement towards statistics learning.

## 4.5. Predictive Relevance

The  $Q^2$  test was developed for the purpose of measuring the predictive relevance of the endogenous variables (Stone 1974), and " $Q^2$  represents a measure of how well observed values are reconstructed by the model and its parameter estimates" (Vinzi 2010).  $Q^2$  was tested by using blind folding procedure, which is a synthesis of function fitting and cross-validation, and the structural models with  $Q^2$  greater than zero are considered to have predictive relevance (Hair *et al.* 2011). Table 8 shows the value of  $Q^2$  for all endogenous constructs.

Table 8: Predictive relevance  $(Q^2)$  for the endogenous constructs

Constructs	$Q^2$
Affect	0.249
Cognitive Competence	0.265
Effort	0.591
Interest	0.560
Statistics Achievement	0.411
Value	0.341

Since the value of  $Q^2$  are greater than zero, which is indicative of a predictive relevance (Vinzi 2010) thus the structural model must be able to provide a prediction of the endogenous latent variables indicators.

#### 5. Discussions and Conclusions

The purpose of this study is to investigate the structural relationship among attitudes of students and achievement towards statistics by examining the hypothesised model i.e. "Attitudes of Students-Achievement Model" in learning statistics. From the ten hypotheses tested, all constructs are supported and the *t*-value obtained shows that they are statistically significant. Through this study, validity and reliability of the measures used are also examined and the findings demonstrated good convergent validity and discriminant validity.

The Difficulty construct has often been used to predict the progresses of statistics learning. The impact of Difficulty on Cognitive Competence is found to be moderate and statistically significant and positive in the structural model (Emmoglu 2011). Many researchers such as Dauphinee et al. (1997), Emmoglu (2011) and Schau et al. (1995) have also found that Cognitive Competence is predicted by Difficulty and was statistically significant and positive. Thus, the attitudes of students-achievement towards statistics model indicates the existence of a positive relationship between Difficulty and Cognitive Competence. Also, the results confirmed that the Cognitive Competence influenced the Affect towards the students' perceptions and attitudes towards statistics. It is noted that the Cognitive Competence was highly correlated with Affect in the model, as has been found in previous research that the relationship between the Cognitive Competence and Affect is also highly correlated (Sorge & Schau 2002; Emmoglu 2011). This means that Cognitive Competence and Affect are closely linked to each other. The relationship between the constructs of Affect and Interest are positive and statistically significant and the findings are in tandem with Emmoglu (2011), Schau et al. (1995) and Tempelaar et al. (2007). Similarly, the impact of Difficulty and Cognitive Competence on Interest are found to be statistically significant and positive.

The results also indicate that the relationship of Interest on Effort, Value and Statistics Achievement are statistically significant. These findings are also supported by other studies such as Emmoglu (2011) and Emmoglu *et al.* (2012). However, there are mixed findings from previous studies on the relationship between Value on Statistics Achievement (Sorge 2001). It is noted that Value had an indirect impact on Statistics Achievement (Nasser 2004). However, the "attitudes of students-achievement towards statistics model" used in this study confirmed the existence of a positive relationship between Value and Statistics Achievement. It is also clear that the Effort is significantly correlated with the Statistics Achievement. In conclusions, the results indicated that all the hypotheses are supported by empirical analysis and in parallel to the previous findings and theoretical framework.

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Faculty of Industrial Sciences and Technology Universiti Malaysia Pahang Lebuhraya Tun Razak 26300 Gambang Kuantan, Pahang DM MALAYSIA E-mail: hassan.r.gh@gmail.com\*, rashid@ump.edu.my, roslinazairimah@ump.edu.my

<sup>\*</sup> Corresponding author