

MALAYSIAN JOURNAL OF MATHEMATICAL SCIENCES

Journal homepage: http://einspem.upm.edu.my/journal

Relationship between Cognitive Factors and Performance in an Introductory Statistics Course: a Malaysian Case Study

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ABSTRACT

This study proposes to determine the impact of three cognitive determinants: prior mathematical knowledge, statistical reasoning and misconceptions on statistical performance using a sample size of 374 Diploma of Science students from a campus of a large Malaysian public university. A quantitative research design was deemed suitable as the objectives of this study were aimed at measuring the strength and direction of the effect of the determinants on students' performance. A survey form was used to collect both primary and secondary data in testing the fit of the hypothesized regression model. The form comprised of items to collect respondent profile information, grades from relevant courses they took previously and self-reported grades of their mathematical achievement and language proficiency in the public examinations. Students' statistical reasoning and misconception were measured through an adapted version of the Statistical Reasoning Assessment (SRA) by Garfield (2003). A linear multivariate regression model was employed to evaluate the strength and direction of the relationships among the factors as hypothesized. Prior Mathematical Knowledge (PMK) (M = 78.54, SD = 11.72) and Statistical Performance (SP) (M=64.63,SD=24.78) were significantly higher as compared to Statistical Reasoning (SR) (M=38.17,SD=13.83) and Misconception (MC) (M=34.44,SD=11.56). Findings also indicated that Statistical Reasoning (SR) and Prior Mathematical Knowledge (PMK) significantly predicted Statistical Performance (SP) but Misconception (MC) did not. The best model generated was SP=14.26+0.579PMK+0.224SR. In addition, MC showed no moderating effect on the presumed relationships. The coefficient of determination for the regression model was $R^2=0.105$ indicating that SR and PMK could only explain 10.5 % of the variance. This low statistic showed that statistical performance is a complex construct that depend not only on other cognitive factors but also non-cognitive variables as well. This paper concludes with a discussion on the pertinent issues related to the administration of the SRA instrument and recommendation for further research in the field of statistical reasoning and performance.

Keywords: Cognitive factors, test performance, regression model, introductory statistics, and Statistical Reasoning Assessment (SRA).

1. Introduction

Malaysian students like many others in parts of South East Asia such as Thailand, and Indonesia do not fare well in statistics achievement. One good source of evidence on this issue is the Trends in International Mathematics and Science Study (TIMSS). Since its inception in 1995 the four yearly studies had shown that mathematical achievement for the fourth (9 years old) and eighth grade (13 years old) in Malaysia were mediocre in comparison to other countries around the world (Gonzales et al. (2008), IEA (2007)). The 2011 TIMSS report (IEA (2007), 2011) showed Malaysia's Eighth Grade mathematics result dropped 34 points from 474 to 440 in 2011 as compared to 2007 while our closest neighbour Singapore recorded an increase of 18 points from 593 in 2007 to 611 in 2011. Furthermore, Malaysia recorded a drop in Data and Chance component for the 2011 study. Comparing the performance of the 2011 cohort of Malaysian students in 4 major content areas, Data and Chance fared the worst in comparison to the other 3 components, i.e., Number, Algebra and Geometry (IEA (2011)). What we are seeing is an obvious dip in the Mathematics and Statistics proficiency of our Form Two students. This trend has been noted since 1999 and it is still sliding (Gonzales et al. (2008)). Hence, this phenomenon is a real cause for concern especially for the teaching and learning of Statistics.

An analysis of the achievement in introductory Statistics for Diploma students in a Malaysian university showed a similar trend. Recent examination report on the achievements of Statistics in a course offered at the diploma level showed a high failure rate. The data for the last 3 semesters highlighted an alarming trend (Zuraida et al. (2012)). This raised a very pertinent question, 'What are the cognitive determinants that predict statistical performance?' This paper hypothesized that three factors, i.e., statistical reasoning, prior mathematical knowledge and misconceptions have significant influence on the student' performance.

From a theoretical perspective, the interplay between the various cognitive factors can be studied using Information Processing Theory (IPT). The model finds parallel in the working of a computer (Plotnik and Kouyoumdjian (2011)). Present day cognitive psychologists are still holding to the dominant view of the 'stage theory' by Atkinson and Shiffrin (1968). This was an important theory to assist researchers to understand the relationship between learning and memory. Learning and memory are complex but necessary cognitive functions. IPT proponents see thinking and mental processes as a kind of structural manipulations of mental representations (e.g. concept, proposition, schema, mental model, mental images and cognitive maps) (Kalat (2011)).

Other cognitive process like problem-solving and reasoning are skills that one develops so that one can act independently as adults. Adults must acquire abilities to source for information, analyze it, and then make reasonable decisions in a rich data-driven environment. How students acquire reasoning and problem solving skills and how they acquire misconception are critical areas of study. A good and logical theory to explain the origin and acquisition of these skills have important educational and practical implications. Cognitive psychologists also believe that the Schema Theory plays an important role in assisting them to understand the thinking and mental processes that go on in the brain (Anderson (1968); Axelrod (1997)). Rumelhart believes that: '. . . schemata truly are the building blocks of cognition. They are the fundamental elements upon which all information processing depends. Schemata are employed in the process of interpreting sensory data (both linguistic and nonlinguistic) in retrieving information from memory, in organizing actions, in determining goals and subgoals, in guiding the flow of processing in the system. (Rumelhart (2011))

It would seem logical to assume that statistical reasoning influences performance in the examination. Those with better reasoning should perform better than those that lack this skill. Unfortunately, this is not the case. There seems to be little correlation between reasoning abilities in Statistics and the students'

performance in the examination. Tempelaar (2004) called this phenomenon the puzzle of 'non-existing relations with course performances'. Garfield (2003) reported low correlation indices for several course outcomes, suggesting statistical reasoning and misconceptions are not correlated to course performance. She found that students may do well in the formative assessments like exam, quizzes and class projects but do not score high on statistical reasoning tests. She hypothesized that there was only surface learning happening and not much of deeper level of understanding due to the present approaches to teaching and learning of statistics. She cautioned that students may seem to do well in getting good grades in both formative and summative assessment, yet still perform poorly in the Statistical Reasoning Assessment.

A study by Zuraida et al. (2012) confirmed this no-relationship phenomenon using aggregated Statistical Reasoning Assessment (SRA) scores. In the 2007 study by Tempelaar and co-researchers, findings showed no relationship between the aggregated scores of statistical reasoning with course outcomes but when they analysed disaggregated levels of the reasoning scores, there was some moderate influence of Statistical Reasoning levels on some of the course outcomes. What was interesting in this study was that the directions of association between different reasoning levels and different content areas, varied. Their research seemed to indicate that scores in statistical reasoning are very much content-specific. For certain topics the learners achieved better results than in others. Tempelaar et al. (2007) hypothesized that a moderating variable is responsible for this no-relationship situation. This study also attempts to determine if statistical misconception could be the possible moderating variable.

2. Methodology

2.1 Sample and Data Collection

A sample of 374 second year Diploma of Science students in a branch campus of a large Malaysian public university who took a course in Statistics for Technology 1 was used. This elementary course in statistics covers basic topics in descriptive statistics and inferential statistics and probability theory. Before the actual study began, a trial version of the SRA was distributed to a small sample of diploma students. The piloting of the instrument was carried out twice. After administrating the instrument, a focus group with 10 students who took the test, was formed. The students were selected based on a set of criteria to ensure maximum output from the group discussions. A set of guided questions were used in the group discussion. The two meetings lasted for about 45 minutes each. The transcriptions were then analysed by comparing similar-

ities and differences of their responses. The group discussions were carried out using both English and *BahasaMelayu* (Malay language), their first language. After some improvements to Garfield's (2003) instrument, it was rerun again. The data collected from the second pilot testing was used to further improve some of the items. Based on these initial findings, a few of the items in the SRA were further modified to suit local needs.

In order to measure students' performance, the grades from their quizzes and tests were recorded. In addition, the score from their final exam was used. There are three factors identified for use in this study. They are Statistical Reasoning (SR), Misconception (MC), Prior Mathematics Knowledge (PMK). The instrument to measure Statistical Reasoning (SR) and Misconception (MC) was the adapted SRA developed after two rounds of pilot testing. Another variable, Prior Mathematics Knowledge (PMK) was measured using the students' grades in Pre-Calculus (MAT133), Calculus I (MAT183) and Calculus II (MAT238), which they took during their last three semesters of their Diploma program. All scores for the independent variables were collected through quizzes, tests, final examination, self-reported grades for SPM results and the SRA instrument. The dependent variable (Statistical Performance (SP)) used the marks from the respondents' final course examination.

2.2 Measures and Instrument

The original SRA consisting of 20 multiple choice items was used to evaluate students' comprehension in basic concepts with a focus on their statistical reasoning skills. Each item in SRA describes a statistics or probability problem, both correct and incorrect. Students were instructed to select the response that best matches their own thinking about each problem.

The adapted version of the SRA investigated 6 correct reasoning subscales (CC1-CC6) and 5 misconceptions subscales (MC1-MC5). The scoring for each subscale was calculated by dividing the total number of correct/incorrect responses by the number of items in that subscale. The score ranges between 0 and 1.

2.3 Data Analysis Procedure: Multiple Linear Regressions

The research methodology is based on an analysis using multiple regression modelling. The model attempts to describe the relations between an outcome variable and some selected response variables. In this study the outcome

variable is Statistical Performance (SP), while the response variables are: Statistical Reasoning (SR), Misconception (MC), Prior Mathematics Knowledge (PMK).

Many multivariate methods are based on the assumption that the data has a multivariate normal distribution. Shapiro-Wilks test and chi-square plot were used to check the assumption of normality. The probability value for Shapiro-Wilks must be more than 0.05 and the skewness value ± 1 .

In order to see which hypothesis can be accepted the test for significance of regression (ANOVA) was carried out. If the observed value of F is large, then at least one variable differs. Statistical tests on individual regression coefficients were assessed. If p-value is less than 0.05, the correlation is considered significant.

3. Findings

This analysis used 374 samples from Diploma of Science students who took Statistics for Technology 1 course. Of particular interest is how such factors as the Statistical Reasoning (SR), Misconception (MC), Prior Mathematics Knowledge (PMK) interact with Statistical Performance. Some summary statistics are given in Table 1 for each variable involved.

The students showed good mastery of prior mathematical knowledge (PMK) at the time of the study (M = 78.54, SD = 11.72) and their mean Statistical Performance (SP) measured at the end of study was well above average (M = 64.63, SD = 24.78). However, the respondents achieved a moderate level of mastery in Statistical Reasoning (SR) (M= 38.17, SD = 13.83) with a significantly high level of Misconception (MC) about statistics (M = 34.44, SD = 11.56). The low scores for both SR and MC are not surprising as the trend is almost similar in other studies in Malaysia or other parts of the world (Garfield (2003); Tempelaar (2004); Tempelaar (2006); Zuraida et al. (2012)).

A correlation matrix (Table 2) was obtained to show the correlations between the selected variables. The correlation between SR and MC is significantly moderate and with a negative sign (r=-0.525, p<0.01). This implied an inverse relationship between the variables, so was the correlation between MC and SP which was weak but significant with an inverse relationship (r=-0.122, p<0.05). The association between PMK and SP was significant and positive (r=0.2772, p<0.01).

Table 1: Descriptive Statistics

						Skewness		Kurtosis	
	N	Min.	Max.	Mean	Std. Dev	Stat.	SE	Stat.	SE
PMK	374	46.75	100.00	78.54	11.72	-0.164	0.126	-0.727	0.252
SP	374	0.00	100.00	64.63	24.78	-0.674	0.126	-0.305	0.252
SR	374	0.00	84.40	38.17	13.83	0.270	0.126	-0.146	0.252
MC	374	0.00	67.30	34.44	711.56	-0.128	0.126	0.202	0.252
Valid N	374								

Table 2: Correlation Matrix

Variable	SP	SR	MC	PMK
SP	1.000			
SR	0.156^{a}	1.000		
MC	-0.122^{b}	-0.525^{a}	1.000	
PMK	0.277^{a}	0.019	-0.025	1.000

^a Correlation is significant at the 0.01 level (2-tailed)

However, the correlation between PMK and SR was not significant (r = 0.019, p < 0.05), so was that of PMK and MC (r = -0.025, p > 0.05). None of the independent variables are strongly correlated to the dependent variable (Statistical Performance) raising questions as to whether there are actually any practical significance or they provide indications of misfits in the regression model.

The correlation values are also found to be less than 0.7 among the independent variables, giving rise to the conclusion that multicollinearity does not exist. In addition Durbin-Watson statistic of 1.923 suggests that multicollinearity is not a problem (see Table 3).

3.1 Assumption Checks

Figure 1 shows a random distribution of data points. Thus it can be concluded there exist linearity, homoscedasticity and normality of residuals. Furthermore, scatterplot and graphs provide further evidence that the assumptions are complied with (see Figure 2 - Figure 4).

The output from Table 3 indicated that approximately 10% of the variance of Statistical Performance (R^2 =0.105, Adj. R^2 =0.095) could be attributed to MC, PMK and SR factors and the ANOVA table (Table 4) showed that the Model 1 was statistically significant ($F_{3,370} = 3.920, p < 0.001$).

^b Correlation is significant at the 0.05 level (2-tailed)

Scatterplot

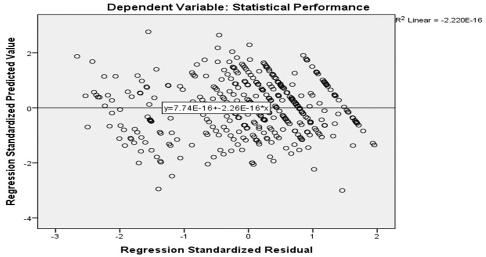


Figure 1: Scatterplot on zpred versus zresid to Check for Normality, Linearity, Homoscedasticity and Independence.

Table 3: Summary Statistics on R Square and Adjusted R Square

Model Summary c

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						Change	Stat.			
Model	R	R^2	Adj.	SE	R^2	F	df1	df2	$\operatorname{Sig}.F$	DW
			R^2		Change	Change			Change	
1	0.318^{a}	0.101	0.094	23.59	0.101	13.920	3	370	0.000	
2	0.323^{b}	0.105	0.095	23.58	0.003	1.297	5	369	0.255	1.923

a. Predictors: (Constant), MC, PMK, SR b. Predictors: (Constant), MC, PMK, SR, zMC_ zSR

c. Dependent Variable: S

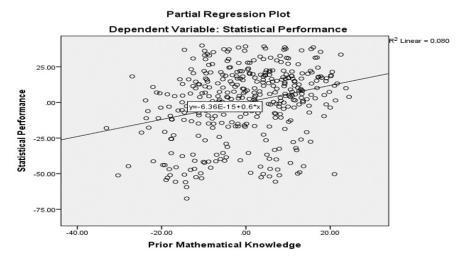
Table 4: Analysis of Variance

ANOVA c								
Model		Sum of Square	df	Mean Square	F	Sig.		
1	Regression	23230.031	3	7743.344	13.920	0.000^{b}		
	Residual	205819.678	370	556.269				
	Total	229049.709	373					
2	Regression	23951.048	4	5987.762	10.773	0.000^{c}		
	Residual	205098.661	369	555.823				
	Total	229049.709	373					

a. Dependent Variable: SP

b. Predictors: (Constant), MC, PMK, SR

c. Predictors: (Constant), MC, PMK, SR, zMC_zSR



 $\label{eq:problem} \mbox{Figure 2: Scatterplot on Distribution of Statistical Performance versus Prior Mathematical Knowledge. }$

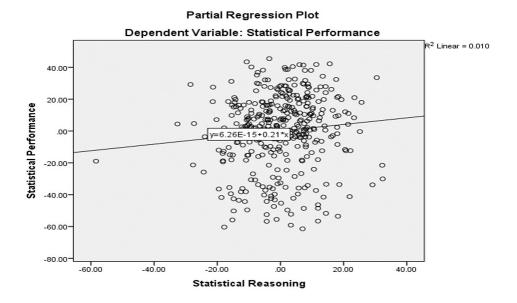


Figure 3: Scatterplot on Distribution of Statistical Performance versus Statistical Reasoning.

Partial Regression Plot

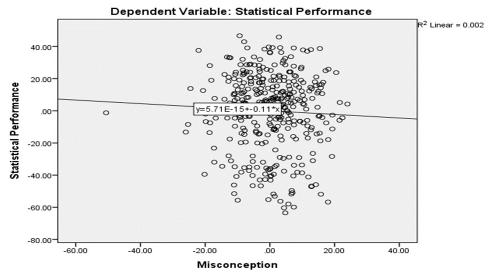


Figure 4: Scatterplot on Distribution of Statistical Performance versus Misconception.

Comparing the R squared and the Adjusted R squared, there is a shrinkage of 0.105-0.095=0.01 or 1% which is comparatively small. This is taken to mean that the model is generalizable using this sample. The effect size (ES) for multiple regression is given by $f^2 = \frac{R^2}{1-R^2}$ (Cohen, 1992). This gives an ES =0.12 which is a medium effect.

3.2 Best Model for The Regression Analysis

In conclusion, the general model takes the form of:

$$Y = B_0 + B_1 x_1 + B_2 x_2$$

where

Y = Statistical Performance (SP)

 x_1 = Prior Mathematical Knowledge (PMK)

 x_2 = Statistical Reasoning (SR)

Table 5: Summary Statistics on Unstandardized and Standardized Coefficients

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		Unstandardized		Standardized		
Model		Coefficients		Coefficients	t	Sig.
		b	SE	beta		
1	(Constant)	14.262	11.001		1.296	0.196
	SR	0.224	0.104	0.125	2.159	0.031
	PMK	0.579	0.104	0.274	5.553	0.000
	MC	-0.105	0.124	-0.049	-0.849	0.397
2	(Constant)	15.339	11.037		1.390	0.165
	SR	0.192	0.107	0.107	1.791	0.074
	PMK	0.578	0.104	0.274	5.553	0.000
	MC	-0.119	0.125	-0.055	-0.952	0.342
	$\rm zMC \times \rm zSR$	-1.161	1.020	-0.058	-1.139	0.255

a. Dependent Variable: SP

The regression model is: SP=14.26+0.579PMK+0.224SR with only PMK ($b = 0.579, SE_b = 0.104, \beta = 0.274, p < 0.001$) and SR ($b = 0.224, SE_b = 0.104, \beta = 0.125, p = 0.031$) being significant contributors to SP while MC ($b = -0.105, SE_b = 0.124, \beta = -0.049, p = 0.397$) has no influence on SP.

Table 5 was generated to investigate whether the association between SP and SR depends on MC. After centering MC and SR and computing the zMC \times zSR interaction term (Dawson, 2014), the two predictors and the interaction term were entered into a simultaneous regression model. Results indicated that SR ($b=0.192, SE_b=0.107, \beta=0.107, p=0.074$) and MC ($b=-0.119, SE_b=0.125, \beta=-0.055, p=0.342$) were not associated with SP. In addition, the interaction between MC and SR was not significant too ($b=-1.161, SE_b=1.020, \beta=0.058, p=0.255$), suggesting that MC does not depend on SR. As such it confirms that MC does not act as a moderator in the relationship between SP and SR.

Although some of these variables were not significant in this model, it may be significant if combined with a different set of IVs. A point to note is that a variable may possess a low weight in the model or may not contribute significantly to the prediction of the model, however it must not be presumed that it is itself a poor predictor (Hair et al. (1998)).

4. Conclusion and Recommendations

The prime objective of this paper was to determine the impact of cognitive determinants like prior knowledge, misconception and reasoning on statistical performance. Findings indicated that Statistical Reasoning (SR) and Prior Mathematical Knowledge (PMK) are significant predictors of Statistical Performance (SP) but not Misconception (MC). This result concurred with previous studies by Chiesi et al. (2010); Lalonde and Gardner (1993); Nasser (2004) and Tempelaar (2006).

The coefficient of determination for the regression model was R^2 =0.105 indicating that Statistical Reasoning (SR) and Prior Mathematical Knowledge (PMK) can only explain a mere 10.5% of the variance. This low coefficient showed that Statistical Performance (SP) is a complex construct that depends not only on many other cognitive factors but also non-cognitive variable as well (Chiesi et al. (2010); Tempelaar et al. (2007)).

According to Tempelaar et al. (2006), reasoning's impact on performance is minimal. However, the results of this study showed that there was a significant effect of statistical reasoning on performance though not strong (r=0.156, p<0.01). These findings are preliminary and need more research to explore this relationship using controlled experiments.

As for the misconception variable, it was found not to play a moderating effect on the relationship between Statistical Reasoning (SR) and Statistical Performance (SP). However, the study shows that misconceptions of the students must not be taken lightly for it is generally high among the respondents and ignoring its role in statistics would have consequences on the outcome of their examination results. This study also showed that Statistical Reasoning Assessment (SRA) can be an effective tool to capture statistical misconceptions of students. Hence SRA can be given to students on the first day of any statistics course and the misconception scores calculated. The scores would provide a good indication of the misconception problem of the learners.

This study has important implications both theoretical and practical. IPT model and schema theory are used as the basis for explaining many of the findings. IPT offers the mechanism to find appropriate educational practices to improve the teaching and learning of reasoning; overcome misconceptions; enhance memory storage; organize information that ultimately lead to better statistical performance.

This study provides some evidence that students' statistical performance in class is a complex construct that has many dimensions to it. Studies have shown many cognitive and non-cognitive determinants like student previous course of study, their grade point average, language skills, self-efficacy, student's attitude towards statistics or student perception of statistics as a tough

subject are responsible (Lalonde and Gardner (1993); Chang and Cheo (2012)). Further research is recommended to look into other cognitive factors and also the influence of non-cognitive factors on performance.

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