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Multilevel analysis of achievement in mathematics of Malaysian and Singaporean students

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Abstract: *This article explored the variation in mathematics achievement of Malaysian and Singaporean eighth-graders as a function of student- and school-level differences. The data obtained from 5314 students nested within 150 schools from Malaysia, and 6018 students nested within 164 schools from Singapore who participated in the Trends in International Mathematics and Science Study (TIMSS) in the 2003. Multilevel linear modeling was employed to analyze the data. The results indicated that 57.28% of the total variance in mathematics achievement in Malaysia accounted for school-level differences. Meanwhile, the results showed that classroom-level differences contributed to 74.6% of the total variance in achievement of Singaporean students. Only 5.9% of the variance in achievement in Singapore accounted for school-level differences. At the student level, mathematics self-concept was the most influential factor on achievement of students from both countries. At the school level, school climate as perceived by the school principals was the most influential factor on achievement of students from both countries.*

Keywords*: Achievement; Factor; Malaysia; Mathematics; Multilevel; Singapore; TIMSS*

1.0 INTRODUCTION

The Trends in International Mathematics and Science Study (TIMSS) is a comparative study designed in 1995 by The International Association for Evaluation of Educational Achievement (IEA). TIMSS was designed to assess the quality of the teaching and learning of mathematics and science among the fourth and eighth-graders across participating countries.

Malaysia and Singapore are two multi-cultural countries having three major ethnic groups: Malay, Chinese and Indians. Singapore is a small island that is 470 times smaller than Malaysia and it is also 6 times smaller than Malaysia in population size. In terms of per capita income, it is almost 6 times higher than Malaysia (Mullis et al., 2004). In spite of these differences, there are some similarities between the education systems. For example, the education system in both countries is centralized. Educational structures and schooling age in both countries are the same and there is no difference in mathematics instruction weekly time. Multi-languages is another common characteristics of the two countries. Even though Malay is the national language of both countries (Quek Gary et al., 2008), however, the medium of instruction in Singapore is English (Mullis et al., 2008; Mullis et al.,2008).

Singapore has joined the TIMSS studies since 1995 at both the fourth and eighth-graders, whereas Malaysia has joined since 1999 only at eighth-graders. Singapore ranked first in the mathematics achievement at the eighth-graders from

TIMSS 1995 to 2003 continuously. The achievement of Singaporean in TIMSS 1999 and 2003 was higher than Malaysia by 91 score in average. In contrast, Malaysia with mean score of 519 in 1999 stood at 16th place among the 38 participating countries, but later improved its ranking to 10th place in 2003 with mean score of 508 among the 45 participating countries. It is worth mentioning that even though the ranking showed improvement from 1999 to 2003, however, this improvement was not due to the status promotion in Malaysia, but rather it was due to the decline in overall mathematics achievements internationally (Mullis et al., 2004; Mullis et al., 2000).

Singapore was a part of Malaysia from the sixteenth to the nineteenth century until it sought independence from Malaysia in 1965 (Noor Azina Ismail & Halimah Awang, 2009). As mentioned earlier, despite many similarities between Malaysia and Singapore, such as the centralization of the educational system, educational structure, allocated instructional time for mathematics, schooling age, race and ethnic groups, Malaysian students performed far lower in TIMSS studies as compared to its counterparts in Singapore. Therefore, the main objective of this study was to explore the factors behind the differences.

2.0 RESERCH QUATRAINS

This research aimed to answer the following research questions:

1. How much of the total variance in mathematics achievement of Malaysian students accounted for student and school-level differences?
2. How much of the student-level variance in mathematics achievement of Malaysian students is associated with mathematics self-concept, attitude towards mathematics and home educational resources factors?
3. How much of the school-level variance in achievement of Malaysian students is associated with school climate, school resources, good attendance at school and the location of the school factors?
4. How much of the total variance in mathematics achievement of Singaporean students accounted for student, classroom and school-level differences?
5. How much of the student-level variance in mathematics achievement of Singaporean students is associated with mathematics self-concept, attitude towards mathematics and home educational resources factors?
6. How much of the classroom-level variance in mathematics achievement of Singaporean students is associated with school climate as perceived by the mathematics teachers?
7. How much of the school-level variance in achievement of Malaysian students is associated with school climate as perceived by the school principals, school resources, good attendance at school and the location of the school factors?

3.0 CONCEPTUAL FRAMEWORK

For the past few decades (1960-1990) many researchers and authors had attempted to find out the answer as to why some students learn better than others and why some schools are more effective than others. Researcher suggests that the possible answer to these questions could be found in educational inputs, processes and context (Huitt, 2003). Consequently, different theories and models (Carroll, 1963; Creemers, 1994; Gage & Berliner, 1992; Huitt, 1995; Proctor, 1984; Shavelosn et al.,1987; Walberg, 1984) were developed and used in studying school effectiveness. In this study, the following conceptual framework shown in Figure 1 which was adapted from Shavelson et al. (1987), served as a guide in selecting the factors for this study.

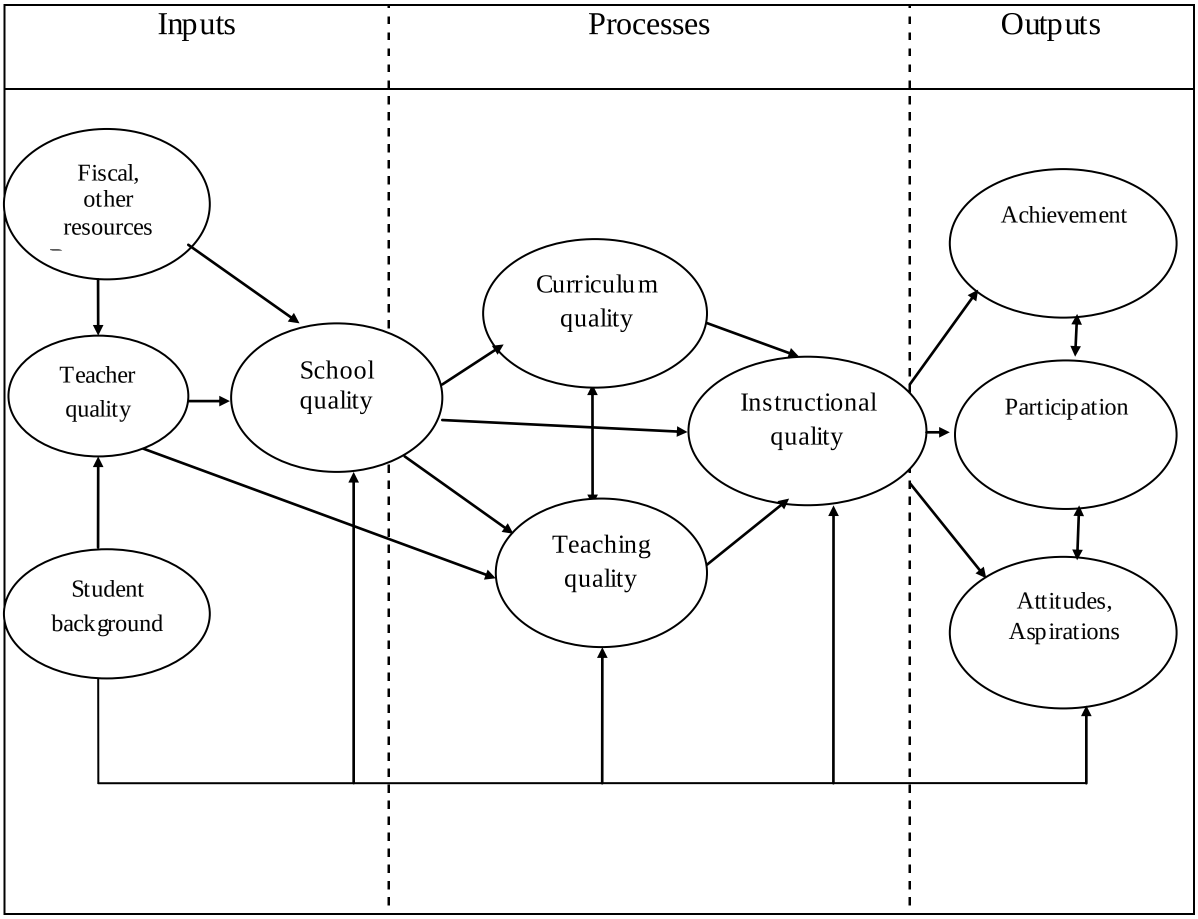

Figure 1: A conceptual model for school effects research

The model contains three main components: inputs, processes and outputs. The inputs refer to the human and financial resources available to education. Processes refer to what is taught and how it is taught. In other words, processes reflect who delivers the instruction, and how the instruction is organized. Outputs refer to what students eventually learned.

The inputs factors such as financial and physical resources, policy-related factors at national, state and school level directly affect the teaching and learning processes of teacher and school quality, which would directly have an effect on outputs. Moreover, students' background at the inputs stage would directly affect teacher quality, teaching quality and school quality and instructional quality in the processes stage, which would eventually, effect the students' achievement at the outputs stage. School quality in turn, has a direct effect on curriculum quality, teaching quality, and instructional quality. Finally, instructional quality has a direct effect on school outputs.

This model is a multilevel model and constitutes three distinguishable levels: student-, classroom- and school-level, and it is deemed appropriate for the analysis of the TIMSS data. As shown in Figure 1, there are many factors which have either a direct or an indirect influence on students' achievement. To consider all of these existing factors in one study was not possible, therefore, based on the model and research evidences only a few factors from student, classroom and school-level were selected to assess their effects on mathematics achievement.

4.0 LITERATURE REVIEW

Learning and teaching process takes place in the classroom, which in turn is situated in school (Leung et al.,2006; Mullis et al., 2005; Oakes, 1989). School environment consists of various elements, ranging from the desk where students sit; to the student who sits next to him/her; and includes the teacher who stands in front of his/her classroom (Coleman et al., 1966; Creemers, 1994).

Several studies have been conducted to answer the question of how much of the variance in mathematic achievement contributes to school-level differences. The results indicate that the proportion of the variance accounted by school-level differences vary across countries. Park and Park (2006) found that in South Korean about 4% of the total variance of mathematics achievement contributed to school-level factors. In contrast, it was 55% for South African students (Howie, 2006). Similarly, Fullarton (2004) reported that 27% and 47% of the variance of mathematics achievement of Australian students accounted for school-level factors in TIMSS 1995 and 1999, respectively. In Singapore 45%, Botswana, 27%, Chili, 35% and Flenders, 14% of the variance of mathematics achievement accounted for school-level factors (Chepete, 2008;

Mohammadpour et al., 2009; Ramírez, 2006; Van den Broeck et al.,2006). Once the researchers had decomposed the total variance of mathematics achievement into student and school-level, they attempted to explain the proportion of the variance at each level by using relevant factors. Thus, some factors such as mathematics self-concept (Kiamanesh, 2004a, 2004b; Ma & Kishor, 1997; Mullis et al., 1997; Mullis et al., 2000; Papanastasiou, 2008; Reyes, 1984; Wilkins, 2004), attitude towards mathematics (Cooper et al., 2001; Goodykoontz, 2008; Kiamanesh, 2006; Ma & Kishor, 1997), home educational resources (Bos & Kuiper, 1999; Coleman et al., 1966; Fullarton, 2004; Howie, 2003; Jencks et al., 1972; Kiamanesh & Mahdavi, 2008) were examined nationally and internationally and the results indicated that there is a positive association between students' achievemnt with mathematics self-concept and attitude towards mathematics.

In addition, a number of school and classroom-level factors such as the location of the school (Chepete, 2008; Howie, 2006; Ramírez, 2006), school climate (Bevans et al., 2007; Cohen et al.,2009; Mullis et al., 2008; Mullis et al., 2004; Papanastasiou & Papanastasiou, 2006), and school resources for mathematics instruction (Ramírez, 2006) were explored to assess the effects of these factors on achievement and it was found that there is a positive relationship between achievement with the location of the school and school climate.

4.0 METHODOLOGY

Sample

TIMSS used a two-stage stratified cluster sampling design. Schools were sampled using a systematic probability-proportional-to-size (PPS), and then one or two classrooms per school were selected (Martin, Mullis, & Chrostowski, 2004). In Malaysia, only one intact classroom was selected among all eighth-graders classrooms within the selected schools. The number of students within a classroom ranged from 19 to 49 with 35 students per classroom on average. All together, the samples from Malaysia were 5314 students, 150 mathematics teachers and 150 school principals participated in TIMSS 2003 study. Singapore added a third sampling stage to the TIMSS's basic two stage and students were selected at random from two classrooms within each selected school. The minimum number of students per classroom was 8 and the maximum was 23 with an average of 18 students per classroom. Thus, a total of 6018 students, 320 mathematics teachers and 160 school principals who participated in TIMSS 2003 were used as samples in Singapore.

Variables

Dependent or predicted variable

TIMSS used a test to measure students' mathematics achievement. Four different types of scores were obtained from the test for individual students: raw scores, standardized scores, national Rasch scores and plausible values or multiple imputation scores (Foy & Olson, 2009). In order to extend the coverage of mathematics curriculum and measuring the trends across TIMSS studies, the TIMSS centre used a large number of mathematics items (190 items). Since the implementation of all 190 items on individual student was not possible, a matrix-sampling design was used to assemble the items into different booklets. Each student sat for a test using only one booklet which included a subtest of all the possible items. TIMSS used Item Response Theory (IRT) scaling to describe students' achievement in the test (Olson et al., 2008). The raw scores were computed based on student's score to the individual items in the booklet. Since students had to answer different items, their difficulty index is not comparable among the students and the raw scores are not reliable for comparison purposes. The raw scores were standardized to a score with a mean of 50 and a standard deviation of 10 within each country. Because of the reasons mentioned above, comparison among students based on standardized scores is still not reliable enough. The national Rasch scores were standardized to have a mean of 150 and a standard deviation of 10 within each country. Finally, the plausible values are an estimate of how a student might have performed if all 190 items were administered to the student. TIMSS estimated five plausible values for individual students based on their responses to a subtest of the items. The plausible values for any given scale are the best available measures of students' achievement on that scale in TIMSS database (Foy & Olson, 2009). Thus, the average of the five plausible values was obtained, and it served as the dependent or predicted variable in this study.

Independent or predictors variables

Mathematics self-concept, attitude towards mathematics and home educational resources are the three student-level factors derived from the Students' Questionnaire. School climate as perceived by the mathematics teachers is a classroom-level factor gained from the Mathematics Teachers Questionnaire. In addition, school climate as perceived by school principals, availability of school resources for mathematics instruction, good attendance at school and the location of the school are the school-level factors obtained from the School Questionnaire. The full characteristics of these factors including items, scale, coding and amount of missing values in each item are presented in Appendix B.

Data Consideration

Normal distribution

The HLM computer package (Raudenbush et al., 2004) produces residual files that could be used to check the distributional assumptions of the data before running the final model. In this study, a probability plot (Q-Q) was used to check the assumption of a normal distribution of the dependent variable. Appendix C displays Q-Q plots for residual errors of students' mathematics achievement of both countries. The plots are approximately linear. This indicates that there is no serious departure from the normal distributions.

Missing data

Missing data are ubiquitous in social and behavioral sciences research due to a variety of reasons (Allison, 2002; Cool, 2000; Dow & Eff, 2009; Enders, 2010; Longford, 2008; Tabachnik & Fidell, 2007) and the TIMSS data are not an exception of missing values. A serious question with regard to missing data is whether missing data is a function of a random or a systematic process (Meyers et al., 2006). If the data are missing completely at random, then deleting cases with missing values does not bias the estimates (Gelman & Hill, 2007), but such strong assumption is rarely satisfied. In these situations, missing values should be modeled to get good estimates of parameters of interest (Allison, 2002; Gelman & Hill, 2007). The next important question concerning missing data is how much data are missing. Tabachnik and Fidell (2007) suggested that if only a few data (i.e., 5% or less) are missing in random from a large data, the problems are less serious and almost any procedure for handling missing values yields similar results. As shown in Appendix B, the amount of missing values in all the items are far less than the size suggested by Tabachnik and Fidell (2007). Missing data is more complicated in multilevel structured data, because it may occur at more than one level. In the case of two-level multilevel modeling, for example, if a level-2 unit (e.g., school) has missing data and then excluded from the analysis, thus, all the observations (e.g., students) that are nested within that unit will be excluded from the analysis (Gibson & Olejnik, 2003). There are only a small amount of missing values in the data being analyzed (Appendix B) and the sample sizes at all the levels of analysis are relatively large (Hox, 2009). However, instead of deleting cases or variables with missing values, the expectation maximization (EM) which is one imputation methods of treating missing data was used to deal with missing values (for detail about imputation methods of missing values see for example; Enders, 2010; Little & Rubin, 2002; Peugh & Enders, 2004; Roth et al., 1999; Rubin et al., 2007).

Weighting issue

As mentioned earlier, TIMSS used a two-stage cluster sampling design rather than a simple random sampling. The probability of selection of sample units at both stages is unequal and sampling weight issue must take into consideration to avoid bias in parameters estimates (Asparouhov, 2005; Dargatz & Hill, 1996; Rabe-Hesketh & Skrondal, 2006; Rutkowski et al., 2010; Thomas & Heck, 2001; Willms & Smith, 2005). TIMSS computes several weighting variables (e.g., TOTWGT, total student weight, SENWGT, student senate weight, MATWGT, mathematics teacher weight). According to Rutkowski et al. (2010), if the data involved in a study is taken from more than one country, student senate weight (SENWGT) should be used. Thus, SENWGT, mathematics teacher's weight (MATWGT) and total school weight (SCHWGT) was used at student classroom and school-level, respectively.

Centering issue

Centering or scaling of independent factors in multilevel analysis refers to subtracting a mean from all individual raw scores on any independent variable and change the raw metric into deviance from the mean score (Tabachnik & Fidell, 2007; Wu & Wooldridge, 2005). According to Kreeft and de Leeuw (1998) the practical purpose of centering an independent variable, is to change the interpretation of the intercept. In multilevel modeling (regression analysis generally), the intercept is defined as the expected score on the dependent variable for someone whose scores on all independent variables in the model are zero (Raudenbush & Bryk, 2002). In social sciences, usually variables have no meaningful zero (Kreeft & de Leeuw, 1998), in such situations, by transferring the independent variables, the intercept will be interpreted as expected score on the dependent variable for someone whose scores on independent variables equal to the group mean or grand mean depending on the type of centering approaches that is used.

The HLM program (Raudenbush et al.,2004) for analysis of multilevel data provides three options to deal with centering of level-1 variable. They are (a) raw metric (uncentered) variable (b) group mean centered and (c) grand mean centered variable. Grand mean centering is the most common method used in multilevel modeling (Enders & Tofighi, 2007; Hox, 2002). Grand mean reduces the multicollinearity among predictors (Hofmann & Gavin, 1998; Kreft, de Leeuw, & Aiken, 1995; Tabachnik & Fidell, 2007). Thus, grand mean centering was used for all the predictor factors in this study.

Data Analysis

The general idea of multilevel modeling is individuals (e.g., students) interact with the contexts (e.g., classroom or school) that they belong to. Students' characteristics are influenced by classroom or school, and the classroom or school in turn influence students' performance. Students and the schools that they belong to are generally conceptualized as hierarchical or multilevel system in which the individuals and the context make up the separate levels of this hierarchy system (Hox, 2002). The TIMSS data have a nested or multilevel structured in which students are nested within classrooms and classrooms in turn nested within schools. It is worth mentioning that however, TIMSS data in nature make three levels (student, classroom and school), because only one classroom per school was sampled in Malaysia, it is not possible to assess the effects of different classrooms within schools. Whereas, individual student was sampled at random from two classrooms within each selected school in Singapore and it provided the possibility of comparing students' mathematics achievement across classrooms within schools. Thus, a two and three-level multilevel modeling approach was employed for analyzing the data from Malaysia and Singapore, respectively using HLM6.07 (Raudenbush et al., 2004).

5.0 RESULTS

The results are presented based on research questions for each country separately.

Malaysia

Research question 1: How much of the total variance in mathematics achievement of Malaysian students accounted for student and school-level differences?

The unconditional or null model was estimated to provide the answer for this research question. This model gives a statistical index which is so-called "intraclass correlation coefficient" (ICC). It is defined as the proportion of the total variance of the dependent variable that attribute to the higher level of the model which is school in the present study (Browne & Rasbash, 2004; Field, 2009; Heck & Thomas, 2000; Raudenbush & Bryk, 2002). The ICC is usually expressed by ρ (rho) and given by this formula $\rho = \tau_{00} / (\tau_{00} + \sigma^2)$. Where, τ_{00} represents the proportion of the total variance at the school level and σ^2 represents the proportion of the total variance at the student level. Thus, the ICC for mathematics achievement of Malaysian students was 2793.31 / (2793.31+2083.40) = 0.5728. This indicated that 57.28% of the total variance of mathematics achievement accounted for school-level and 42.72% (1-0.5728) by student-level differences.

Student-level models

Research question 2: How much of the student-level variance in mathematics achievement of Malaysian students is associated with mathematics self-concept, attitude towards mathematics and home educational resources factors?

To assess the effect of individual factors on mathematics achievement, the factors were added to the model separately and the results are presented in Table A.1 of Appendix A. Mathematics self-concept was added to the model first (model 1). This factor accounted for 14.36% of student-level variance of mathematics achievement. The effect of mathematics self-concept on achievement was statistically significant ($\gamma_{10} = 32.08$, $p < 0.001$). This indicates that students with one scale-point higher on self-concept tend to achieve 32 points higher in mathematics. Mathematics self-concept served as a random effect and the result indicated that the relationship between self-concept and mathematics achievement varied significantly from school to school ($u_{1j} = 75.28$, $p < 0.05$).

Attitude towards mathematics was the second factor that entered to the model (model 2). Attitude accounted for a negligible amount of the variance (0.69) when the effect of mathematics self-concept was controlled. The effect of attitude was statistically significant (γ_{20} = 6.72, $p < 0.001$). One scale-point increase in positive attitude towards mathematics increases achievement by 6.72 points. The relationship between attitude towards mathematics and achievement varied significantly from school to school (u_{2j}= 47.86, $p < 0.05$).

An index of home educational resources was the last factor that added to the model (model 3). Model 3 accounted for only a small proportion of the variance (0.002) controlling for mathematics self-concept and attitude towards mathematics. The effect of home educational resources was not statistically significant (γ_{30} = 3.70, $p > 0.05$).

School-level models

Research question 3: How much of the school-level variance in achievement of Malaysian students is associated with school climate, school resources, good attendance at school and the location of the school factors?

The location of the school was the first factor added to the model (model 4). The contribution of this factor to the school-level variance was 5%. The effect of the location of the school was statistically significant (γ_{01}= 25.19, $p < 0.05$). This indicated that students from urban schools achieved higher scores in mathematics than their peers from rural schools by 25.19 points.

School climate as perceived by the school principals was the second factor that added to the model (model 5). This model accounted for 4.77% of the school-level variance after controlling for the location of the school. Mathematics achievement affected significantly by this factor (γ_{02}= 19.97, $p < 0.05$). Average mathematics achievement was higher by 19.97 points in schools where the principals described the climate of the school positively. School climate as perceived by the mathematics teachers was also a significant factor on achievement (model 6). It accounted for 5% of the school-level variance controlling for the location of the school and school climate as perceived by the school principals. The effect of this factor on mathematics achievement was statistically significant (γ_{03} = 21.47, $p < 0.05$). Average mathematics achievement was higher by 21.47 points in schools where the mathematics teachers described the climate of the school positively.

School resources for mathematics instruction and good attendance at school were the last two factors that added to model 7 and 8, respectively. The school resources factor accounted for 3.78% of the school-level variance after controlling for the location of the school and school climate as perceived by both the school principals and mathematics teachers. The association between this factor and mathematics achievement was significantly negative (γ_{04} = -13.92, $p < 0.05$). Average mathematics achievement decreased by 13.92 points in schools with one scale-point more shortage in resources for mathematics instruction.

Good attendance at school explained 1.21% of the school-level variance of mathematics achievement after controlling the factors location of the school, school climate as perceived by both the school principals and mathematics teachers and school resources. The association between these factor with mathematics achievement was also negative, but it was not statistically significant (γ_{05}= -18.49, $p > 0.05$).

In order to assess the effects of student and school-level factors on achievement simultaneously, all the factors were added to the model (full model). The full model accounted for 14% of the student-level variance and 25% of the school-level variance in achievement.

Singapore

Research question 4: How much of the total variance in mathematics achievement of Singaporean students accounted for student, classroom and school-level differences?

The unconditional model was estimated to provide answer for this research question (Appendix A, Table A.2, null model). The ICC at each level is:

For the student level, $\sigma^2/ (\sigma^2 + \tau_\pi + \tau_\beta)$ = 1165.67/ (1165.67+4496.51+358.13) = 0.193

For the classroom level, $\tau_\pi/ (\sigma^2 + \tau_\pi + \tau_\beta)$ = 4496.51/ (1165.67+4496.51+358.13) = 0.746

For the school level, $\tau_\beta/ (\sigma^2 + \tau_\pi + \tau_\beta)$ = 358.13/ (1165.67+4496.51+358.13) = 0.059.

The results indicated that 19.3%, 74.6% and 5.9% of the total variance in mathematics achievement of Singaporean eighth-graders accounted for student, classroom and school-level differences, respectively.

Student-level models

Research question 5: How much of the student-level variance in mathematics achievement of Singaporean students is associated with mathematics self-concept, attitude towards mathematics and home educational resources factors?

Three models were estimated to answer this research question and the results are given in Appendix A, Table A.2.

Again, mathematics self-concept was the first factor that was entered to the model as a random effect (model 1). It accounted for 22.77% of the total student-level variance. Mathematics self-concept affected achievement significantly (γ_{100}= 24.23, $p < 0.001$). The relationship between self-concept and mathematics achievement varied significantly from classroom to classroom within schools (u_{00k} = 28.41, $p < 0.05$), but it was not from school to school (u_{10k} = 3.95, $p > 0.05$).

Attitude towards mathematics was added to the second model (model 2). Attitude accounted for 5.33% of the student-level variance controlling for mathematics self-concept. The association between attitude towards mathematics and achievement was statistically significant (γ_{200}= 10.87, $p < 0.001$).

Home educational resources factor was introduced to the model (model 3). Model 3 accounted for a negligible amount (0.33) of the student-level variance when mathematics self-concept and attitude towards mathematics were controlled. The effect of home educational resources on achievement was statistically significant (γ_{300} = 11.01, $p < 0.001$).

Classroom-level model

Research question 6: How much of the classroom-level variance in mathematics achievement of Singaporean students is associated with school climate as perceived by the mathematics teachers?

Model 4 was estimated with school climate as perceived by the mathematics teachers. This model accounted for 3.50% of the total classroom-level variance of mathematics achievement. The effect of this factor on achievement was statistically significant (γ_{010}= 20.49, $p < 0.05$). This indicated that, on average, mathematics achievement in classrooms where teachers described the climate of the school positively; was higher by 20.49 points than other classrooms.

School-level models

Research question 7: How much of the school-level variance in mathematics achievement of Singaporean students is associated with school climate as perceived by the school principals, school resources for mathematics instruction and good attendance at school factors?

School climate as perceived by the school principals was the first factor that was added to the model (model 5). This factor contributed to a substantial (54.53%) proportion of the school-level variance in mathematics achievement. The effect of school climate as perceived by the school principals on achievement was statistically significant (γ_{001}= 29.70, $p < 0.001$).

Model 6 was estimated by adding school resources for mathematics instruction. Model 6 accounted for 17.30% of the school-level variance after controlling for school climate as perceived by the school principals. However, the effect of school resources on achievement was not significant (γ_{002}= -13.54, $p > 0.05$). Model 7 was estimated by adding the factor of good attendance at school; it explained 3.42% of the school-level variance after controlling for school climate as perceived by the school principals and school resources for mathematics instruction. The effect of good attendance at school also was not statistically significant (γ_{003}= -4.33, $p > 0.05$).

A full model was estimated by adding all the factors from the three levels. The full model was accounted for 27.13%, 15.62% and 35.36% of the variances at student, classroom and school-level, respectively.

6.0 DISCUSSION

The results indicated that 57.28% of the total variance in mathematics achievement of Malaysian eighth-graders accounted for school-level differences. Likewise, a greater proportion of the variance in mathematics achievement in the Singapore sample was attributed to classroom and school-level differences (74.6% to classroom level and 5.9% to school-level). This is one the key results of the study and it indicated that schools make a difference in students' achievement in both countries. An interesting finding of this study is not only that mathematics achievement of Singaporean students differed from school to school, but it also differed substantially from a classroom to another within a school. It is more important for Singaporean students to be placed in a particular classroom within a school rather than being assigned to a school they are placed in. According to Anderson (1991), school effectiveness depends to a great extent on teacher effectiveness. Teachers have absolute veto power over innovation and change even in the most highly centralized educational system. Therefore, what happens in classrooms could be accounted for this great difference in students' achievement.

School effects on students' academic achievement have been subjected to a considerable debate among educational researchers for a long time. Early studies, for example, Coleman et al. (1966) and Jencks et al.(1972) on school effectiveness revealed that the effects of school on students' academic achievement is relatively small compared to the effects of students characteristics and family background. Following Coleman et al.'s (1966) report, several studies Chepete (2008), Fullarton (2004), Howie (2006) and Park and Park (2006) for example, have been done to assess the effects of school on mathematics achievement of students. It was found that a sizeable proportion of the total variance in mathematics achievement attributed to school-level differences. The proportion of the variance that attributed to school-level differences in this study is beyond the range found in recent studies. The findings of this study added evidence to those from previous studies that schools make a difference in students' academic achievement. This findings have key implications for educational policy-makers, because, school has control over most of the classroom and school-level factors such as those examined in this study. On the other hand, student-level factors (e.g., home educational resources and other family background factors) are not under the control of school.

Mathematics self-concept, attitude towards mathematics and home educational resources altogether accounted for 15.32% of the total variance in mathematics achievement of the Malaysians at the student level. In contrast, these three factors accounted for 28.43% of the total variance in mathematics achievement of the Singaporean students at the student-level. This indicated that these factors are more effective on achievement of Singaporean students than for the Malaysians. Mathematics self-concept among other student-level factors was the most influential factor on achievement of students from both countries. This confirms the findings by Howie (2003), Kiamanesh, (2004b; 2005), Ma and Kishor (1997), Papanastasiou (2008), Wilkins (2004). The effect of mathematics self-concept on achievement differed for the Malaysians and Singaporeans. Mathematics self-concept was more effective for the Singaporeans in terms of the explained variance, but the association between this mathematics self-concept and achievement was stronger for the Malaysians.

Attitude towards mathematics was the second strongest factor that affected achievement of Malaysian students positively, whereas it was the third strongest factor in the Singaporeans achievement. Attitude towards mathematics was more effective factor on achievement of Singaporean students than the Malaysians. Home educational resources had no significant effect on achievement of Malaysia students as it did for the Singaporeans, although the contribution of this factor to the variance in achievement of Singaporean students was very low. This is an interesting finding especially for Malaysian students. Because generally, Singaporeans have an advantage of having home educational resources more than Malaysian, but the contribution of home educational resources was negligible to the variance of mathematics achievement of the Singaporeans. The five factors of the location of the school, school climate (both perceived by the mathematics teachers and the school principals), school resources for mathematics instruction and good attendance at school accounted for 19.76% of the total variance of Malaysian students at school-level. On the other hand, the three factors of school climate as perceived by the school principals, school resources and good attendance at school explained 75.25% of the total variance at school-level.

The location of the school had a great effect on mathematics achievement of Malaysian students where students from urban schools performed much better than those from rural schools. This result is consistent with Howie's (2006) findings. This result was expected because rural students are more disadvantaged than urban students in terms of family background and having access to limited educational resources. Singapore is an urban based country, thus the location of the school was not a factor in Singapore.

School climate as perceived by school principals was the most influential factor for both countries. However, this factor accounted for a substantial proportion of the variance in achievement of Singaporean students than the Malaysians. School resources for mathematics instruction had no significant effect for the Singaporeans whereas, it did for Malaysians. One possible explanation for this finding is probably that all Singaporean schools are well equipped with instructional resources such as computer, audio-visual resources and library materials. In contrast, Malaysian schools are different to some extent in terms of the availability of resources for mathematics instruction.

6.0 CONCLUSION

The results of this study revealed that mathematics achievement of Malaysia eighth-graders is motivated mainly by differences from school to school. Mathematics achievement of Singaporean eighth-graders is motivated mainly by differences from classroom to classroom within school. Mathematics self-concept among other student-level factors was the most influential factor on achievement of students from both countries. The location of school among other school-level factors was the most influential factor on achievement of Malaysian students. This was followed by school climate as perceived by the school principals. For the Singaporeans, school climate as perceived by the school principals among other school-level factors was the most influential factor. Shortage of school resources for mathematics instruction affected mathematics achievement of Malaysian students negatively, whereas it was a significant factor for the Singaporeans.

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