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The Effectiveness of Smart Schooling in terms of Student Achievement in Science: A study of Malaysian Practice

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This paper reports the relative effectiveness of Smart and Mainstream schooling in terms of student achievement in science. The participants comprised 770 secondary school Form 3 (15-year-old) students from two Smart Schools and two Mainstream Schools in Malaysia. Using students' Standardised National Examination (SNE) primary-school science achievement results as covariate, SNE lower-secondary science achievement results were analysed using analysis of covariance (ANCOVA). The results indicated that the level of achievement in science of Form 3 students in the Smart Schools was statistically significantly higher than their counterparts in Mainstream Schools with an educationally significant effect size of +0.41. A "statistical triangulation" was provided through follow-up analyses using ANCOVA by school and independent t-tests by entry grade. The former confirmed that the significant group difference was indeed contributed by both Smart Schools while the latter revealed that group difference in science achievement was strongest amongst students with B and C entry grades. The paper discusses the findings in terms of parallel impact comparison within the available literature and recommends that future studies should look into isolating specific elements of the Smart Schools Initiative that have direct impact on student science achievement.

***Key words**:* Smart schools; Achievement; Science education

Introduction

The *smart school* was originally conceived by Perkins (1995) as responding to social needs for deeper learning through employing educational approaches informed by new perspectives in cognitive science. This label and many of Perkins' central ideas were embraced by the Malaysian government in its Smart Schools Initiative launched in 1999. In accord with Perkins' model of a pedagogy of understanding, the Malaysian Smart School was conceived as developing "content knowledge, problem solving knowledge, epistemic knowledge, and inquiry knowledge" (Smart School Pilot Team [SSPT], 1997, p.31). The influence of Perkins' notion of meta-curriculum could be seen in the initiative's emphasis on explicit teaching of skills for creative and critical thinking. In line with Perkins' emphasis on the physical, social and symbolic distribution of intelligence, the initiative envisaged new information and communication technologies helping to "combine the best of network-based, teacher-based and courseware materials" (SSPT, 1997, p.58), through "every computer… [and] have access to the latest educational materials available locally, as well as to external resources" (SSPT, 1997, p.102).

Around the world, similar government initiatives seek to strengthen schooling provision in pursuit of an economic vision of sustained, productivity-driven growth achieved through building a scientifically and technologically literate, critical thinking workforce. All too rarely, however, is the implementation and effectiveness of such initiatives researched, particularly where they occur outside highly developed countries. For example, although the Malaysian Smart Schools Initiative has now been in operation for over a decade, the Ministry of Education has yet to publish any official evaluation of its impact on student achievement, although there have been reports about the upgrading of schools (e.g. Timbuong, 2009), and about infrastructure development and utilisation, particularly with regard to information and communication technology (ICT) (e.g., Norrizan, 2007). We suspect that this Malaysian situation has commonalities with similar developments in other educational systems, so that research into it has the potential to provide insights of wider interest. This paper will focus on what many regard as the crucial question about the impact of such initiatives: their effect on student achievement. Specifically, it reports a study which examines the effectiveness of science teaching in Smart Schools, as compared to Mainstream Schools, in terms of student science achievement.

The Malaysian Smart School: An Overview

The Malaysian Ministry of Education launched its Smart Schools Initiative in 1999 involving a total of 90 pilot – mainly secondary – schools across the country. Support from the Ministry for participating schools included funding for infrastructure development, particularly in setting up computer laboratories, and upgrading teachers' pedagogical expertise through in-service courses.

The official definition of a Smart School is "…a learning institution that has been systematically reinvented in terms of teaching-learning practices and school management in order to prepare children for the Information Age" (Smart School Project Team [SSPT], 1997, p.10). This philosophy of on-going transformation considers that "the Smart School concept itself is still a work in progress and remains open to evolutionary refinement, including advances in pedagogy and improvement in information technology" (SSPT, 1997, p.9).

In overlaying newer reform ideas on earlier ones, the Malaysian Smart School Initiative introduced tensions. For example, official guidance advocated both constructivist practice and mastery learning, without clarifying how these might be reconciled in a coherent pedagogical approach. Equally, the detail of reform ideas and their operationalisation was often underdeveloped. For example, official guidance provided only short generalised descriptions of information technology-enabled approaches in science teaching. In many respects, the Smart Schools Initiative has been an emergent reform.

Our research has been able to characterise implementation of smart schooling through classroom observation, teacher interview and student report (Ong & Ruthven, 2010). The distinctive features of science teaching in Smart Schools were found to be a near absence of the note giving and copying prevalent in Mainstream Schools, replaced by ICT-mediated and student-centered teaching approaches, often intertwined to provide extended support for learning. Thus the technology-enriched environment of the Smart Schools provided support for self-directed, self-paced, and self-accessed learning. While the overarching topic was usually teacher-specified, students were able to choose and pick a learning task from the available range of activities to work on, contingent upon their current level of ability and interests. They were able to work on the learning task, individually or jointly, progressing at their own pace.

Science Achievement: A Review

Research studies on the influence of student science achievement of pedagogical innovations or reforms that share certain common characteristics with the Smart Schools Initiative were reviewed. Achievement in this context is mainly taken to refer to the acquisition of science content.

Von Sector and Lissitz (1999) investigated the impact of three pedagogical reforms, namely providing more opportunities for laboratory inquiry, increasing emphasis on critical thinking, and reducing the amount of teacher-centred instruction, on student science achievement. The science achievement measure, developed by Educational Testing Service (ETS), consisted of science questions drawn from the fields of biology, earth science, physics, and chemistry. It purported to measure "high-order thinking as well as understanding of fundamental concepts and mastery of basic skills" (Von Sector & Lissitz, 1999, p.1114). The combined effect of the instructional practices was found to be associated with higher science achievement.

However, these researchers also observed some unintended consequence of such instructional strategies in contributing to greater achievement gaps among students with different demographic profiles. Firstly, the use of laboratory inquiry was invariably associated with higher achievement overall and with more equitable achievement among students from different demographic profiles provided that they had equal access to laboratory facilities, equipment, and supplies. A corollary to this finding is the explanation for the failure among at-risk students in disadvantaged schools in terms of lack of resources and training for teachers contributing greatly towards that failure. This observation was reinforced by the findings of Supovitz and Turner (2000) that underscore the importance of professional development as a means of improving student science achievement. Here, the quantity of professional development and also teachers' content preparation are shown to be strongly linked to both inquiry-based teaching practice and investigative classroom culture.

Von Sector and Lissitz (1999) found no evidence that emphasising critical thinking is associated with significant differences in mean science achievement. They attributed this finding to measurement error that failed to reveal systematic differences between schools, rather than a true lack of instructional impact on science achievement. However, indirect effects of critical thinking on achievement as a result of interaction with student gender and minority status were observed. Contrary to its intended outcome of more equitable distribution of achievement, an emphasis on critical thinking was associated with a magnification of gender and minority gaps. This finding suggests that on average, females and minorities are more at risk of low achievement in schools where teachers are encouraged to embrace critical thinking.

Interestingly, Von Sector and Lissitz (1999) found teacher-centred instruction to be negatively associated with socio-economic status (SES), favouring the science achievement of low-SES students. However, these researchers pointed out the danger of drawing causal inference from such associational results, and argued that teacher-centred instruction did not cause inequity in achievement associated with SES. Offering a possible explanation for this association, these researchers hypothesised that perhaps the low-SES students were more likely to be low achievers who were not yet able to work independently on complex tasks and actually benefited from cognitive scaffolding provided by more structured, teacher-centred environments.

The results from Turpin's (2000) study indicated that the science achievement of students involved in the activity-based Integrated Science (IS) programme was significantly higher than the science achievement of students involved in the traditional science programme. Equally, Wideen (1975) found a significant difference in science achievement between students in the SAPA (Science – A Process Approach) programme and students in the traditional science programme, favouring the former.

In examining the relative effectiveness of guided versus unguided computer-based instruction with respect to regular instruction, Ardac and Sezen (2002) found that, while computer-based instruction (with or without teacher's guidance) was observed to be more effective than regular instruction in improving process skills particularly amongst high-achieving students in chemistry, students in the unguided condition failed to construct the expected content knowledge as compared to students who received regular or guided computer-based instruction. Using *The Growth Curve of Microorganisms* computer simulation programme amongst tenth graders, Huppert, Lomask, and Lazarowitz (2002) found that the concrete and transition operational students in the experimental group achieved a significantly higher academic achievement than their corresponding counterparts in the control group, suggesting the potential impact a computer simulation programme can have in enabling students with low reasoning abilities to cope successfully with learning concepts and principles in science which require high cognitive skills.

Blosser (1984) maintains that science achievement is influenced by a whole range of variables when she notes, "students scored higher who were from higher socio-economic home backgrounds, who had better reading ability, who had better scholastic abilities, who were less mobile, and who had taken more course work related to the test than those who did not possess these characteristics" (p.518). The highest correlation seems to be with student scholastic ability and socio-economic background. Together, these account for about 20-50% of the variance. Other factors, such as student interest and attitude toward the subject being assessed, emphasis on skill development (mastery learning), and amount of instructional time related to goals and objectives, need to be taken into account when considering student achievement.

In summary, student science achievement seems to be influenced by many variables that include pedagogical or curricular innovation, socio-economic background, interest, and scholastic ability. Hence the importance of taking into account some of the moderating factors and also providing a description of the teaching and learning process in the existing programmes so as to make a more valid comparison of student science achievement.

Methodology

Research Design

A comparative design in a realistic school setting (Styles, 2006) was used to compare the effectiveness of science teaching in Smart and Mainstream Schools in terms of student science achievement. From official evaluations conducted while this study was being designed, it had also become clear that quality of implementation was varied among institutions. This study, then, set out to examine examples of what was officially judged to be the best available practice to be found amongst the 46 non-selective neighbourhood secondary schools then designated as Smart Schools.

Purposive Sampling of Schools

To gain access to schools, and secure the cooperation of teachers, it was expedient to carry out the study in the region of Malaysia where the first author was professionally active. Two Smart Schools – one in Penang, one in Perak – were recommended by officials in the Ministry of Education on the basis of reports from on-site monitoring of science teaching in Smart Schools as part of a national evaluation; this had led to science teaching in these schools being ranked first and fifth respectively in the evaluation, with both (what we shall refer to as) SS1 and SS2 rated as meeting the criterion that "teachers operationalised Smart teaching and learning of science well and successfully", and SS2 rated as approaching the further criterion that "teachers operationalised Smart teaching and learning of science in an excellent manner and seemed to internalise it in their daily pedagogical practice".

To provide a benchmark for comparison, a non-selective neighbourhood Mainstream school located near to each Smart School was chosen, with a student body of similar composition by race, gender, and socio-economic status. It should be noted that, in Malaysia, placement of students in non-selective secondary schools is arranged by the respective District Education Offices on the basis of catchment area. Indeed, students in the cohort examined in this study had already been allocated to secondary schools before their designation as Smart Schools.

Science Achievement Instrumentation

Lower Secondary Assessment, known as *Penilaian Menengah Rendah* (PMR) in its Malay equivalent, was taken by all Form 3 (15 year-old) students to gauge their levels of attainment in core and elective subjects taught in Forms 1 to 3. The Malaysian Examinations Syndicate, which is part of Ministry of Education (MoE) Malaysia, coordinates this national assessment.

Science was one of the core papers of the PMR and will be referred to subsequently as Science PMR. Comprising 75 multiple-choice questions that were drawn from the content areas covered in Forms 1-3 as specified in the science syllabuses, Science PMR was administered to all Form 3 students over duration of one hour and thirty minutes. Given that it tests according to the specified content in the syllabuses, Science PMR has high content validity. The reliability of Science PMR was assumed since it was developed and administered nationally by the MoE-owned examination body.

Data Collection Procedures

Students' Year 6 science achievement results in the Standardised National Examination (henceforth referred to as UPSR science achievement) were accessed from school records. This measure served as the entry grade level, or covariate in further data analysis. This cohort of students sat for the PMR in October 2003 with the results announced in December 2003. Since PMR was conducted by the Malaysian Examinations Syndicate with stringent security measures taken to avoid leakage and its on-site administration, which involved teachers from neighbouring schools to assume the invigilation tasks, the proper administration of Science PMR Paper was assumed.

Data Analysis Procedures

The Science PMR was scored by the Malaysian Examinations Syndicate. The result for each individual student was reported in one of the following grades: A, B, C, D, E and X. The grades and their corresponding denotations are given in Table 1. For scoring, A=5, B=4, C=3, D=2, E=1, and X=0.

Table 1
Grading in Science PMR

Grade	Denotation
A	Distinction
B	Credit
C	Good
D	Achieved the minimum level of mastery
E	Failed to achieve the minimum level of mastery
X	Did not sit for the paper

Analysis of Covariance (ANCOVA), a method of "statistical analysis that combines the analysis of variance with regression analysis" (Glass & Hopkins, 1996, p. 593), was used as the primary inferential statistical analysis to test the research hypothesis. In the analysis, the dependent variable was student achievement as indicated by Form 3 scores on Science PMR. The students' SNE scores in science taken in Year 6 served as the covariate. A ninety five percent level of confidence ($p < .05$) was used as the criterion for statistical significance.

In a naturalistic setting, despite efforts made to equate the two groups (e.g., selecting Mainstream Schools that matched Smart Schools in terms of student general ability, location, and race composition) prior to the study, there are bound to be some differences between the schools. According to Borg and Gall (1983), use of ANCOVA addresses the problem of pre-existing group differences as it reduces the effects (of initial group differences) by making compensating adjustments to the post-test means of the two groups. In addition to ANCOVA, effect size (ES) was also calculated as "an aid to interpret the results of a single study …[and] for making inferences about the practical significance of research results" (Borg & Gall, 1983, p.385). In lending support, Rennie (1998) notes that, "because statistical significance does not imply practical significance, researchers are urged to address the issue of practical significance in reporting their results" (p.238). Plucker and Ball (1996) point out that such practical significance could and should be demonstrated using effect sizes. Furthermore, comparing the Smart and Mainstream groups in terms of effect size "will give the reviewer a better understanding of the phenomenon under investigation" (Borg & Gall, 1983, p.198). Mathematically, ES = [(Adjusted Smart Mean) – (Adjusted Mainstream Mean)]/(Pooled Standard Deviation).

The dataset was initially screened for normality, linear relationship between covariate and dependent variable, and homogeneity of regression slopes. If any of the necessary assumptions was not met, other appropriate statistical technique(s), data transformation, or outlier deletion were performed accordingly.

Results

Entry Profile Screening

The students' Year 6 UPSR science achievement results were used as the entry level (covariate) in ANCOVA. Table 2 shows the distribution of entry grades by group and school.

Table 2
Distribution of Entry Grades by Group and School for PMR Science Achievement Analysis

Entry Grade	Smart Schools			Mainstream Schools		
	SS1	SS2	Total	MS1	MS2	Total
A	24	26	50	15	4	19
B	52	100	152	60	34	94
C	106	25	131	140	73	213
D	40	0	40	24	28	52
E	10	0	10	4	5	9
Total	232	151	383	243	144	387

As shown in Table 2, the initial difference between the Smart and Mainstream Schools in terms of students' entry grades favours the former. Although ANCOVA seeks to take account of such initial differences (Ferguson & Takane, 1989; Glass & Hopkins, 1996; Hinkle, Wiersma, & Jurs, 1998) by making compensating adjustments to the post-test means of the two groups, it was desirable to undertake complementary statistical analyses to triangulate these findings.

It is the entry profile of SS2 (Smart School 2) which is primarily responsible for the differences between groups; the profile of SS1 (Smart School 1) is much more similar to those of MS1 (Mainstream School 1) and MS2 (Mainstream School 2). First, in order to make a convincing case that the results from the ANCOVA for science achievement can reasonably be interpreted as the outcome of differences between Smart and Mainstream science teaching, a further analysis of covariance by school was performed. The entry profile of SS2 lacks students graded D or E, and this produces a corresponding imbalance in the grade profiles of the two groups. Second, independent t-tests for each entry (covariate) grade of student are performed so as to establish a like-for-like comparison in which the scores obtained in PMR science achievement for students in Smart Schools are compared to those students in Mainstream Schools with identical entry grades. This type of stratification strategy has been proposed by Pedhazur and Schmelkin (1991), and employed by Post, Gilljam, Rosendahl, Bremberg, and Galanti (2010). By identifying differences among students with comparable levels of prior achievement, it enables a more accurate determination of the impact of various predictor variables on the dependent variable. In particular, this strategy helps to minimize the impact of differences in prior science achievement because each analysis involves students for whom such achievement is similar.

As observed in Table 2, there is a very small sample size at the E entry grade. According to Kraemer and Thiemann (1987), the number of participants is directly related to power, where power is the ability to detect "real" differences (i.e., correctly reject the null, when an alternate hypothesis is true). Furthermore, Cohen (1988) recommends 80% power achievable through having 30 participants per cell, as the minimum power for an ordinary study. Therefore, the independent t-test for students at E entry grade should be given little weight.

These complexities arise because the data are drawn from a real-world situation. However, by analysing the data in these different ways, it should be possible to draw firmer conclusions.

Data Screening

Data screening on UPSR science achievement (or, covariate) and PMR science achievement (or, post-test) for normality and other statistical characteristics are given in Table 3.

Table 3
Mean, Median, Mode, Skewness and Kurtosis for Interval Variables

Variables	N	Mean	Median	Mode	SD	Skewness	SE (Skewness)	Kurtosis	SE (Kurtosis)
Pre-test	775	2.67	2.65	3.00	0.89	0.14	0.09	0.02	0.18
Post-test	770	3.01	3.00	2.00	1.16	-0.36	0.09	-0.98	0.18

Table 3 shows that the values of skewness and kurtosis fall within the acceptable range of not more than +1.00 or not less than –1.00 (Morgan, Griego, & Gloeckner, 2001), suggesting that none of the distributions was markedly skewed and that they were neither too peaked with long tails nor too flat with too many cases in the tails. Taken together, this indicates that the use of parametric methods was appropriate.

While there was a linear relationship between the covariate (i.e., UPSR science achievement) and dependent variable (i.e., PMR science achievement), the interaction testing for homogeneity of regression slopes showed that there was a significant interaction between group and covariate [$F_{(1, 766)} = 5.32$, $p < .05$]. Therefore, the homogeneity of regression slopes could not be assumed. Accordingly, ANCOVA was used with caution in this analysis. As a precautionary measure, two supplementary statistical analyses were computed to crosscheck the adjusted group mean difference of ANCOVA. Firstly, the ANCOVA by school was performed to establish that the group differences found was indeed contributed by both Smart Schools. Secondly, the independent t-tests by covariate grade were performed to provide a better understanding of the results of ANCOVA, comparing identical students in terms of entry grade between Smart and Mainstream Schools.

Results of Statistical Analysis

As shown in Table 4, the analysis of covariance by group yielded an F-ratio of 53.83 that was statistically significant ($p = .000 < .001$) and an effect size of +0.41 that was educationally significant. The adjusted mean obtained for the Smart Schools (3.25) was statistically significantly higher than the adjusted mean obtained for the Mainstream Schools (2.77). Therefore, the research hypothesis that the science achievement of Form 3 students who had participated in the Smart Schools is higher than the science achievement of Form 3 students who had participated in the Mainstream Schools is accepted.

Table 4
Results Obtained from Analysis of Covariance by Group for Science Achievement

Analysis of Covariance							
Source	Sum of Squares	df	Mean Squares	F	p		
Group	42.47	1	42.47	53.83	.000		
Pre	323.50	1	323.50	409.99	.000		
Error	605.29	767	0.79				
Mean							
		Covariate		PMR Science Achievement			
Group	N	Mean	SD	Mean	SD	Adjusted Mean	Δ^*
Smart	383	3.50	0.94	3.37	1.14	3.25	0.41
Mainstream	387	3.16	0.80	2.64	1.05	2.77	
Total	770	3.33	0.89	3.01	1.16		

* Δ , effect size (ES) = (adjusted Smart mean – adjusted Mainstream mean)/(pooled SD of 1.16)

An effect size of 0.41 signifies that the average student in the Smart Schools performed at about 0.4 of a standard deviation above the average person working in the Mainstream Schools.

However, to examine whether the group difference found was contributed by both the Smart Schools, an ANCOVA by school was performed.

Table 5
Results Obtained from Analysis of Covariance by School for Science Achievement

Analysis of Covariance					
Source	Sum of Squares	df	Mean Squares	F	p
School	56.55	3	18.85	24.39	.000
Covariate	246.38	1	246.38	318.86	.000
Error	591.11	765	0.77		

Mean						
		Covariate		PMR Science Achievement		
School	N	Mean	SD	Mean	SD	Adjusted Mean
SS1	232	3.17	0.98	2.98	1.12	3.09
SS2	151	4.01	0.58	3.97	0.89	3.51
MS1	243	3.24	0.78	2.69	1.10	2.75
MS2	144	3.03	0.83	2.56	0.98	2.77
Total	770	3.33	0.89	3.01	1.16	3.03

Pairwise Comparisons		
School (I) – School (J)	Mean Difference (I-J)	p$^+$
SS1 – SS2	-0.41	.000 **
MS1 – MS2	-0.02	1.000
SS1 – MS1	0.34	.000 **
SS1 – MS2	0.32	.004 *
SS2 – MS1	0.76	.000 **
SS2 – MS2	0.74	.000 **

* Significant at $p < .05$
** Significant at $p < .001$
\+ Adjusted for multiple comparisons: Bonferroni

As shown in Table 5, the analysis of covariance by school yielded an F-ratio of 24.39 that was statistically significant ($p < .001$), suggesting a significant difference in at least one of the pairwise comparisons. The post hoc tests (see Table 5) revealed that SS1 and SS2 achieved significantly higher adjusted mean scores than each of the Mainstream Schools. Evidently, the significant group difference reported earlier was indeed contributed by both Smart Schools.

Further insight and understanding of the relative effects of Smart and Mainstream science teaching can be gained if an independent t-test is performed to compare the PMR science achievement of students with each of the covariate (UPSR science achievement) grades.

The bar chart in Figure 1 show the mean score difference in PMR science achievement between students in Smart and Mainstream Schools at each grade level in UPSR science achievement. Visually, these suggest that students with UPSR grades A – D performed better in Smart Schools whereas students with UPSR grade E performed worse.

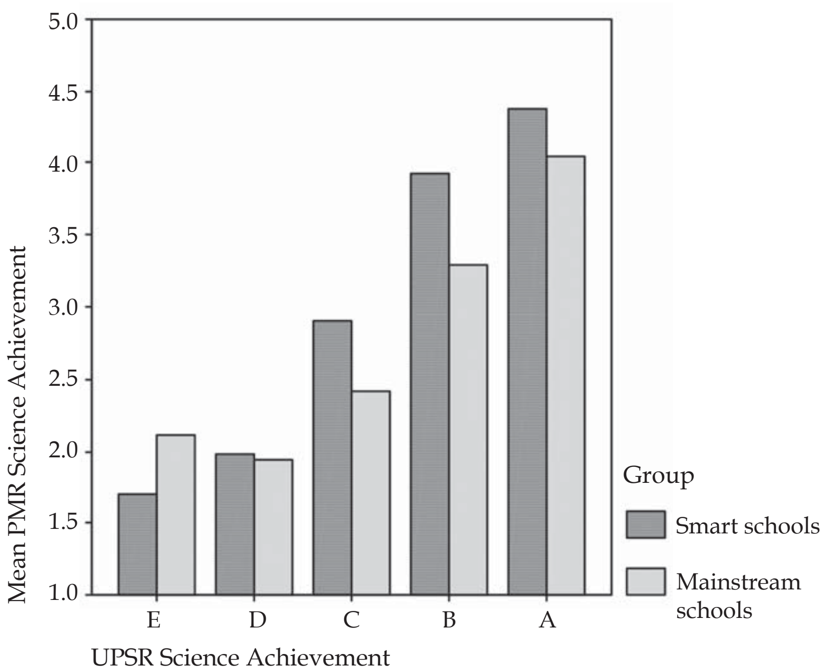

Figure 1. Bar chart for group mean PMR science achievement score differences by UPSR science achievement.

As given in Table 6, the results of the independent t-tests revealed that only at grades B and C did students in the Smart Schools perform significantly higher than did their counterparts in the Mainstream Schools. Furthermore, the effect sizes for group differences at D, C, B and A entry grades show a 'curvilinear' trend with D indicating the smallest and non-significant value, followed by the significant and educational meaningful effect sizes of 0.55 and 0.63 at C and B entry grades, but end with a non-significant but educationally meaningful effect size of 0.33 at A entry grade. This elucidates the failure of the assumption of homogeneity of regression slopes. Little weight should be given to the comparison at E grade, however, because it involved only a very small sample size.

Table 6
Results Obtained from Unpaired Samples t-Test for PMR Science Achievement by UPSR Science Achievement Grade

UPSR Science Achievement Grade	Smart Schools			Mainstream Schools					
	N	Mean	SD	N	Mean	SD	t	p	Δ+
A	50	4.38	0.81	19	4.05	1.43	0.94	.357	0.33
B	152	3.93	0.85	94	3.29	1.14	4.69	.000*	0.63
C	131	2.90	0.91	213	2.42	0.81	5.06	.000*	0.55
D	40	1.98	0.62	52	1.94	0.46	0.29	.772	0.08
E	10	1.70	0.48	9	2.11	0.78	-1.40	.181	-0.62
Total	383	3.37	1.14	387	2.64	1.05			

* significant at $p < .001$
+ Δ , effect size (ES) = (Smart mean – Mainstream mean)/(pooled SD)
[Note: 1.01, 1.02, 0.88, 0.53, 0.66 are pooled SDs for A, B, C, D, and E graders respectively]

Conclusion and Discussion

The ANCOVA results for the PMR science achievement scores showed that the Form 3 students involved in the 3-year Smart Schools Initiative had a significantly higher adjusted mean score compared to students involved in the Mainstream Programme. The students from Smart Schools achieved a 0.48 point higher adjusted mean score on the PMR science achievement compared to students in Mainstream Schools [3.25 and 2.77 respectively, $F_{(1, 767)} = 53.83$, $p < .001$]. Such a difference is also educationally significant given the obtained effect size of +0.41, which is equivalent to approximately two fifths of a standard deviation. This finding was supported by follow-up analyses using ANCOVA by school and independent t-tests by entry grade. The former confirmed that the significant group difference was indeed contributed by both Smart Schools while the latter revealed that group difference in science achievement was strongest amongst students with B and C entry grades.

Accordingly, in terms of impact, the results indicated that students in the Smart Schools achieved a significantly higher adjusted mean score than did the corresponding students in the Mainstream Schools. We have not been able to find any previous studies with which these findings could be directly compared. However, the science achievement outcome in this study is consistent with earlier research on science achievement and activity-based programmes (i.e., Turpin, 2000; Wideen, 1975), and science achievement and computer-based learning (i.e., Ardac & Sezen, 2002; Huppert et al., 2002).

While it seems plausible that the use of ICT and extended support learning associated with smart science teaching are responsible for better science achievement, it is salutary that these effects are limited to A, B, and C graders. It may be that more strongly teacher-supported extended support for learning will be necessary to improve science achievement amongst low achievers on entry to secondary school.

In interpreting these findings it is important to recall that the two Smart Schools were chosen on the basis that they had already been judged particularly effective, with the Mainstream Schools then chosen simply on the basis of their matching demographic characteristics. Such purposive sampling provided an assurance that some smart teaching processes would be observed. Had we opted for randomisation in selecting two Smart Schools, we could have ended up having Smart Schools which were only "smart" by designation and not in actual practice. Consequently, the positive outcome in science achievement can plausibly be related to smart science teaching. Although observation indicated that the actual implementation fell a long way short of the aspired smart science practice (Ong, 2004), the outcome from the comparative effect, with the two Mainstream Schools serving as a baseline, suggests the worth of smart science teaching.

Further studies investigating similar impact of Smart Schools Initiative using a more nationally representative sample are recommended in order to support generalisation. Further study is also needed to determine if similar results can be found in other grade levels, particularly amongst students in Year 6, Form 5 (Year 11 equivalent), and Upper 6 (Year 13 equivalent) who would be sitting for the corresponding Standardised National Examinations. Since this study only utilised Form 3 students, it would be valuable if future studies included students at all grade levels across primary education, lower secondary education, upper secondary education, and the two-year sixth form education to determine how students at these different levels respond to the Smart Schools Initiative. Equally, it would be beneficial to determine the lasting impact of the Smart Schools Initiative by examining if students continue to show gains in successive years of implementation.

The Smart Schools Initiative promotes the use of ICT alongside other smart teaching elements such as constructivist practice, mastery learning, self-accessed, self-paced and self-directed learning. Additional research is needed to determine which smart teaching elements have greatest effect on science achievement variable. Equally, given that the impact of various possible combinations of these smart teaching elements remains unclear, further study to isolate the relative impact, be it positive or otherwise, of these possible combinations would be illuminating and beneficial. It would also contribute significantly to the research and literature if the future research could determine whether other ICT-based science programmes have a similar impact science achievement compared to the Smart Schools Initiative.

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