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ABSTRACT

Using Walberg's educational productivity model, this study estimated the influences of home environment, motivation, ability, classroom environment, quality of instruction, and instructional time on mathematics outcomes using longitudinal data from the Second International Mathematics Study (SIMS). SIMS was a comprehensive survey of the teaching and learning of mathematics in 20 countries conducted by the International Association for the Evaluation of Educational Achievement. The data incorporated measures collected at the beginning and the end of the academic school year. The U.S. sample comprised 7,935 eighth-grade 13-year-old mathematics students in 299 classrooms. Results indicate that attitude toward mathematics can be reliably assessed as mathematics outcome and that instructional time is a significant direct influence upon both mathematics achievement and attitude. Contains 18 references. (MKR)

The Enduring Effects of Productivity Factors on Eighth Grade Students' Mathematics Outcome

by

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ABSTRACT

Using Walberg's educational productivity model, the study estimated the influences of home environment, motivation, ability, classroom environment, quality of instruction, and instructional time on mathematics outcome by using longitudinal data from the IEA's SIMS sample of eighth grade U.S. students. The data incorporated measures collected at the beginning and the end of the academic school year. The U.S. sample comprises 7,935 thirteen year old eighth grade mathematics students in 299 classrooms. Twenty countries took part in this large scale longitudinal study. Results are discussed in terms of their theoretical significance and practical implications.

The Enduring Effects of Productivity Factors on Eighth Grade Students' Mathematics Outcome

Recent studies have suggested that the average scores obtained by American children, especially in mathematics and science, are consistently below those obtained by children from many other countries (Dossey, Mullis, Lindquist, & Chambers, 1988; International Association for the Evaluation of Educational Achievement, 1988; McKnight et al., 1987; Stevenson, Chen, & Lee, 1993; Stevenson, Lee, & Stigler, 1986; Walberg, 1984). These findings have prompted calls for educational reform and for further research on factors associated with the relatively poor performance of American children (see U.S. Department of Education, 1987). It seems that mathematics outcome, at least as measured by mathematics achievement and mathematics attitude, has suffered in American schools, a situation that seems more alarming considering that Education may be America's largest enterprise (Walberg, 1984). Thus the title of the commission's report--"A Nation at Risk"--seems appropriate.

Weiss (1987) explains that despite concentrated studies in mathematics in elementary schools that one-quarter of the country's 9-year-olds fail to reach the beginning level defined by National Assessment of Educational Progress--a level characterized by the ability to add and subtract two-digit numbers. To support Weiss' finding, Mullis, Owen, and Phillips (1990) added that only one-fifth of the country's 9-year-olds show a grasp of all four basic numerical operations--addition, subtraction, multiplication, and division. They explain that once the low-achieving students are at a disadvantage that they rarely catch up to the curriculum, but instead appear to fall farther and farther behind.

At the high-school level, large proportions of students choose to avoid mathematics courses and, to an even greater extent, science courses. Though the United States may retain a larger percentage of students in high school than many other countries, the Second International Mathematics Study found that advanced mathematics course enrollment in the United States was only about average (Gilford, 1987; Weiss, 1987).

Several studies show that causes of mathematical success or failure are multifactorial. The variables may have important direct or indirect effects of mathematics outcome. All the variables may be interrelated, affecting each others as well as mathematics outcome (Reynolds & Walberg, 1992a, b, c; Stevenson, 1987; Stevenson, Lee, & Stigler, 1986). McKnight et al. (1987) assert that single causes of mathematical failure are "deceptive explanations." This assertion was based on comparative data among twenty countries participating in the SIMS. Sources of failure, such as, the amount of time for mathematics instruction, the teacher and status of the teacher, the quality of teaching, class size, and the comprehensive curriculum in American public schools did not account for poor performance in mathematics. They therefore conclude that educational deficit is a complex problem that is influenced by many factors.

In a study comparing U.S., Japanese, and Taiwanese students, Stevenson (1987) found that at the beginning of the first year of schooling that all groups were equal on cognitive scores. But, after the first year of schooling, Asian students outscored American students. In addition, the academic performance of the worst Asian class exceeded that of the best American class by the completion of five years of schooling. These findings seem to suggest that multiple factors seem to influence the excellent academic performance of Asian students. The factors include the students' involvement in more rigorous curriculum, coverage of more material at a faster pace, more time allocated for academic studies, and parental encouragement and support for academic endeavors. Additionally, Asian students attribute their academic success to hard work, while their American counterparts attribute theirs to ability (Stevenson, 1987).

Stevenson (1987) found that elementary schools in Asia usually compensate for differential learning rates of their students. Typically, Asian students are required to understand material presented in class, and, accordingly, the students work assiduously to master mathematical concepts. These basic attitudes about human performance appear to influence Asian students' academic success. Both McKnight et al. (1987) and Stevenson (1987) identified attitudinal factors as influencing achievement. Their comparisons were reported as cultural or national differences.

Findings from these and other recent studies (Miller & Miyake, 1990; Reynolds & Walberg, 1992a, 1992b, 1992c; Stariha, 1989) report that cognitive, affective, and environmental factors seem to contribute to superior academic performance. As research questions become more focused on multiple influences and outcomes, one can respond by using

TABLE 1

Nine Factors of Educational Productivity

A. Student Aptitude

1. Ability or prior achievement as measured by the usual achievement tests

2. Development as indexed by chronological age or stage of maturation

3. Motivation or self-concept as indicated by personality tests or the student's willingness to persevere intensively on learning tasks

B. Instruction

4. Instructional time or the amount of time students engage in learning

5. The quality of the instructional experience including method (psychological) and curricular (content) aspects

C. Psychological Environments

6. Home Environment or the "curriculum of the home"

7. Classroom environemnt or the morale of classroom social group

8. The peer group outside school

9. Minimum leisure-time television viewing

multidimensional learning models that incorporate attitudinal and environmental components to the conventional achievement and instructional ones.

One way of examining multiple influences and outcomes across several variables is to employ a model of educational productivity. The model makes it clear that no single factor alone can produce marked increases in academic learning. The model is based on an economic theory of national, industrial, and agricultural productivity. In a simple model of economic productivity, productivity is defined as the product of input and output (Walberg, 1984).

Walberg (1984) developed an educational productivity model by expanding on previous multivariate productivity models, such as Carroll's (1963) conceptual model and Bloom's (1976) Mastery learning model. Educational productivity model deals with the interaction of the factors affecting success in school learning. The model is illustrated in Table 1. It includes three categories: student aptitude, instruction, and psychological environments. Within the three categories were nine productivity factors. When optimized the factors are able to increase affective, behavioral, and cognitive learning. The categories are powerful, consistent, and generalizable because they are based on the synthesis of over 3,000 studies of the factors that influence school learning (Walberg, 1984). The factors affect each other in varying degrees and in turn influence student learning.

The present study extends Walberg's (1984) model by following the sample over a one-year period in order to assess the power of the model to predict mathematics outcome at the eighth grade level, when it is assumed that the students were completing middle school and were ready for high school work. Using Walberg's educational productivity model, the study estimated the influences of home environment, motivation, ability, classroom environment, quality of instruction, and instructional time on mathematics outcome by using longitudinal data from the IEA's SIMS sample of eighth grade U.S. students.

The first purpose of this study was to examine the validity of the individual and structural variables of the productivity model. The second purpose was to extend the model to consider not only achievement but also attitudes toward mathematics as outcomes. Though student outcomes have traditionally been classified into two broad domains: cognitive (sometimes called intellective) and affective (sometimes called non-cognitive) yet, according to Astin (1991), educators tend to shy away from assessing affective outcomes because they think think affective outcomes are too value laden. They feel much more comfortable limiting their assessments to cognitive outcomes. Students' attitudes toward a school subject is one of the affective outcomes that had been under assessed. Despite the underassessment, during the last half century several studies have revealed the increasing student alienation from science and mathematics courses during the adolescent years (Walberg, 1991). The third purpose was to determine the degree to which the productivity factors (1) directly influence mathematics achievement and attitude and (2) serve as mediators for the indirect influence of prior factors.

Method

Model

The structural model estimated in the present study is shown in Figure 1. It depicts mathematics achievement and attitude as outcomes of a four-phase sequence of effects beginning with the home environment. The home environment influences student-aptitude variables (motivation and mathematics ability (or attitude)) at the beginning of eighth grade as well as mathematics outcome at the end of eighth grade. The home environmental effects on aptitude variables are mediated by social psychological and instructional environments. The structure is consistent with the popular belief that what parents do with their children at home seem to impact on what the children do at school. These parental impacts may help the children even as much as ten years along the road. According to Redding (1992), the curriculum of the home consists of patterns of habit formation and attitude development that prepares children for academic learning and sustains them through the schooling years. It would not be surprising them to expect home environment to influence motivation and motivation and mathematics ability directly. Home environment would be expected to influence initial attitude directly but not the final attitude (attitude towards mathematics) because the effects on the latter is mediated by other variables.

Strong psychological evidence exists that students learn better, learn more, and remember longer when they find pleasure in the learning experience (Bloom, Hasting, & Madaus, 1971). Motivation has been shown as the single most important of the nine productivity

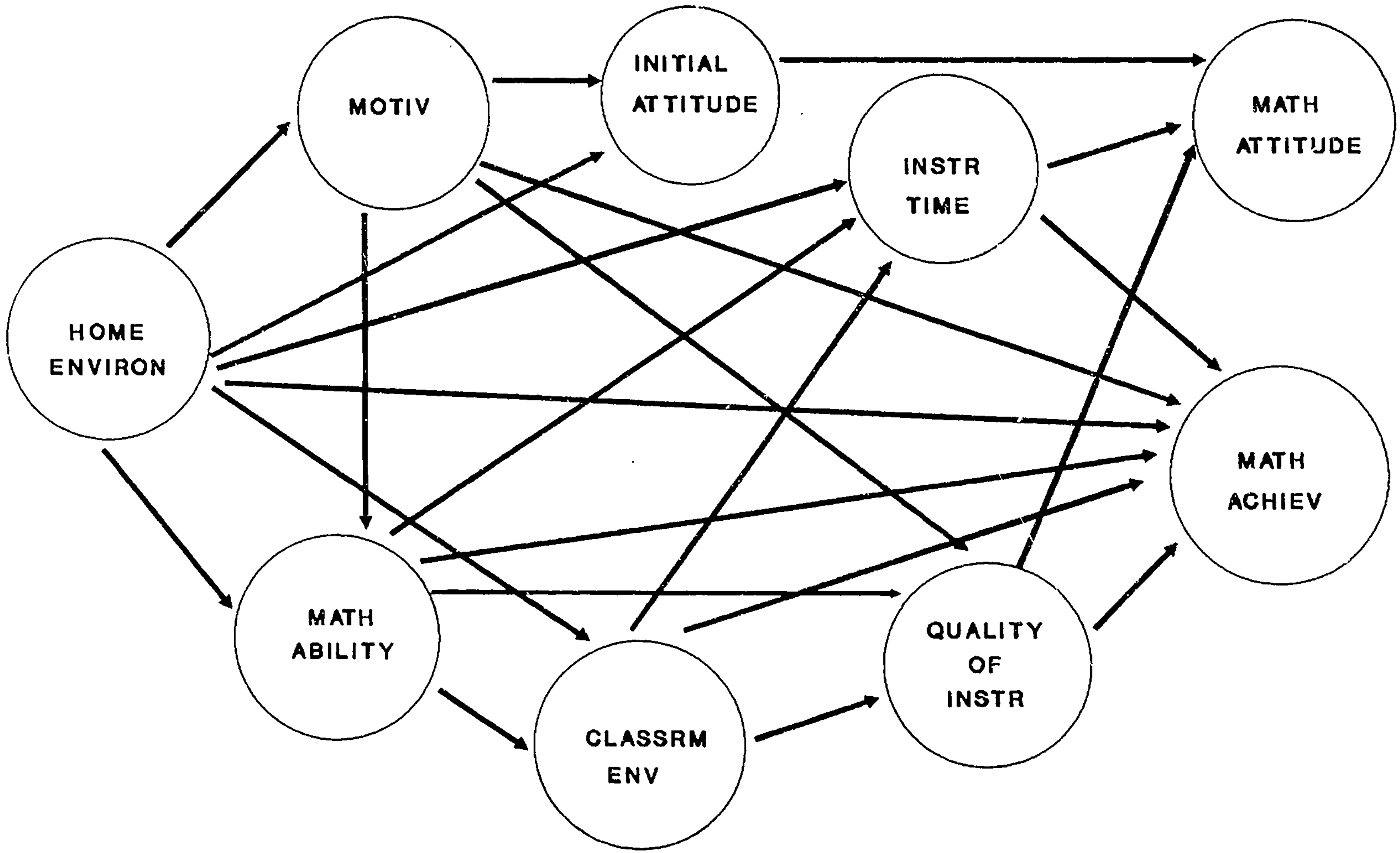

Figure 1. Educational Productivity Model of Math Outcome

factors (Blumenfeld et al., 1982, Brophy, 1981). Motivation would be expected to directly influence mathematics ability and initial attitude towards mathematics and not the psychological environment of the classroom because its effect on the classrooom environment is mediated by mathematics ability. The remaining factors exert their effects a bit later, with classroon environment preceding instructional effects (instructional time and quality of instruction). Bloom (1976) explains that instructional influences depend in part, on student attributes and behaviors.

As explained above, the model was extended to include initial and final attitudes toward mathematics. Attitudes are considered important factors in education and it was expected that their path of influence would be similar to that of achievement, in that home environment and motivation were expected to be strong direct influencers of initial attitude (Bloom, 1976).

__Sample__

Data for this study were drawn from the Population A cohort of thirteen year old U. S. students, in the eighth grade, who participated in the longitudinal study of the Second International Mathematics Study (SIMS). SIMS was a comprehensive survey of the teaching and learning of mathematics in 20 countries conducted by the International Association for the Evaluation of Educational Achievement. The United States was one of eight countries participating in the longitudinal portion of the SIMS survey, in which achievement and attitudinal data were collected by administering tests and questionnaires at the beginning and end of the 1981-82 academic year. In addition, extensive data were collected from questionnaires distributed at the end of the academic year, in which students responded to numerous items related to their self-concept and backgrounds. The population from which the United States sample was drawn was all the eighth grade students in mainstream public and non-public schools in the United States. A seven stage weighted sample was drawn from this population. Two grades per school were selected as target classrooms. The highly stratified seven-stage national probability sample consists of 7,935 thirteen year old eighth grade mathematics students in 299 classrooms. Students, teachers, and principals from each targeted school participated in the study.

This sample represents a general cohort of students who were approaching the time when would make their first decisions about continuing the study of mathematics (McKnight et al., 1987).

Specifying the Structural Model

In the following section, the model was specified by describing the observed and latent (or observed) variables included. As recommended by Harris and Schaubroeck (1990), multiple observed indicators were used to measure most of the latent constructs in the model. The variables were selected from the items contained in the SIMS logitudinal data file.

There were no items in the data file representing peer group influence outside the school or television viewing time. Also, since the students were from the same grade level, age was relatively constant and therefore was omitted. Therefore, only six of the nine educational productivity factors were used in the study.

<u>Home Environment</u> represents the intellectual and emotional behaviors that parents provide to stimulate their children's general development and school learning. The observed indicators of this variable were parental support, parents' occupation, and parents' education. Parental support was constructed by summing nine items assessing students' opinions about parents' attitude toward mathematics (α=.73). Parents' occupation and parents' education were each constructed by taking the means of two items (α = .70, α = .72 respectively).

<u>Mathematics Ability</u> represents the prior achievement of students at the beginning of the eighth grade. As noted, students were administered an achievement at the beginning and end of the 1981-82 academic year. These tests contained a core of 40 items covering the areas of arithemetic, algebra, geometry, probability and statistics, and measurement (coded: 1 = correct, 0 = not correct). Mathematics ability was measured as the sum of those items correctly answered on the test at the begining of the year (α = .89). The tests administered in SIMS "represent an international consesus as to what mathematics is expected to be taught and learned. For the Unted States, the curricular fit of the tests were generally satisfactory for the grade levels used in the study" (McKnight et al., 1987, p. 5). Furthermore, in the development of items for the test, special attention was paid to include items on topics that would be sensitive to growth during the school year (Travers & Westbury, 1989).

<u>Initial Attitude Toward Mathematics</u> was constructed by summing eight items assessing students' opinions about mathematical strategies:

two items each on "solving word problems;" "memorizing rules and formulas;" "estimating answers to problems;" and "checking answer by going back over it" (all items were reverse coded) (α = .65).

Motivation was measured with a two item self-concept scale ("I am not so good at mathematics" (reverse coded) and "I am looking forward to taking more mathemtics;" α = .77) and a one item on the students' perseverance in learning mathematics ("I will work a long time in order to understand a new mathematics idea").

Classroom Environment was measured with one item asking about the students' comprehension of mathematics class: "I usually understand math class."

Quality of Instruction was measured with a one-item learning opportunity scale on the use of four-figure calculator (coded: 1 = only within home, 2 = only math class, 3 = only other class, 4 = 1 + 2 only, 5 = 1 + 3 only, 6 = 2 + 3 only, 7 = all three, 8 = no (8 recoded as 0)) and a six-item study aids scale on the use of educational materials (coded as above and also with "8 recoded as 0" (α = .78).

Instructional Time was measured with a four-item homework time scale (coded actual number of hours spent doing homework) (α = .81) and a two-item math instruction time scale (coded actual number of hours spent on extra mathematics tutoring) (α = .68).

Outcome variables were mathematics achievement and attitude towards mathematics. Mathematics achievement, administered at the end of the academic year, was measured as the sum of items answered correctly among 40 core items covering the areas of arithemetic, algebra, geometry, probability and statistics, and measurement (coded:

1 = correct, 0 = not correct). Students' measure of mathematics achievement would reflect gains, if any, in knowledge accumulated over the academic year (α = .91). Attitude toward mathematics, like initial attitude toward mathematics, was constructed by summing eight items assessing students' opinions about mathematical strategies: two items each on "solving word problems;" "memorizing rules and formulas;" "estimating answers to problems;" and "checking answer by going back over it" (all items were reverse coded) (α = .71). Students' measure of attitude toward mathematics would reflect changes, if any, in mathematics attitude over the academic year.

Data Analysis

Two goals of the analysis were to estimate the relative strength of the proposed variables in explaining mathematics outcome (achievement and attitude) and to assess how much variance in mathematics outcome could be accounted for by the variables in the structural model. A polychoric/polyserial correlation matrix among observed variables was estimated with PRELiminary LISrel (PRELIS, Jöreskog & Sörbom, 1988). Polychoric/polyserial correlations yield the best estimates of linear association for variables measured on ordinal scales or mixed scales (ordinal and interval) as departure from normality may be present (Pearson product-moment zero-order correlations underestimate the "true" correlations) (see Table 2). Following Jöreskog and Sörbom's (1989) recommendations for categorical data, the weighted least squares (WLS) fitting function of LISREL-7 (LInear Structural RELations) was used to estimate the parameters of Walberg's productivity model.

TABLE 2

Listwise Polychoric and Polyserial Correlations Between Observed Variables Included in the Model

	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10
Self-Concept (X1)	1.000									
Perseverance (X2)	0.210	1.000								
Mathematics Ability (X3)	0.217	0.012	1.000							
Classroom Environment (X4)	0.490	0.121	0.253	1.000						
Word Problems-1 (X5)	0.213	0.119	0.064	0.095	1.000					
Memorize Rules-1 (X6)	0.202	0.118	0.075	0.121	0.251	1.000				
Estimate Answers-1 (X7)	0.138	0.112	0.008	0.072	0.302	0.203	1.000			
Check Answers-1 (X8)	0.105	0.155	0.106	0.006	0.303	0.285	0.213	1.000		
Calculators (X9)	0.004	0.003	0.144	0.012	0.022	0.005	0.011	0.005	1.000	
Study Aids (X10)	0.020	0.007	0.130	0.001	0.011	0.009	0.009	0.014	0.343	1.000
Homework Time (X11)	0.039	0.131	0.103	0.024	0.113	0.122	0.073	0.119	0.015	0.045
Extra Tutorial (X12)	0.005	0.074	0.082	0.064	0.042	0.012	0.027	0.073	0.000	0.039
Word Problems-2 (X13)	0.297	0.194	0.128	0.197	0.406	0.152	0.177	0.181	0.000	0.029
Memorize Rules-2 (X14)	0.303	0.216	0.051	0.121	0.237	0.334	0.148	0.182	0.003	0.022
Estimate Answers 2 (X15)	0.214	0.167	0.012	0.104	0.187	0.123	0.364	0.156	0.029	0.016
Check Answers-2 (X16)	0.176	0.256	0.098	0.079	0.253	0.220	0.183	0.433	0.024	0.026
Math Achievement (X17)	0.230	0.007	0.784	0.285	0.067	0.092	0.039	0.102	0.147	0.086
Parental Support (X18)	0.210	0.182	0.035	0.162	0.123	0.125	0.123	0.126	0.030	0.067
Parents' Occupation (X19)	0.045	0.017	0.284	0.069	0.000	0.042	0.019	0.055	0.080	0.089
Parents' Education (X20)	0.077	0.005	0.336	0.100	0.033	0.047	0.008	0.074	0.075	0.077

Note: Coefficients > .062 are significant at $p < .05$

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TABLE 2 (contd.)

Listwise Polychoric and Polyserial Correlations Between Observed Variables Included in the Model

	X11	X12	X13	X14	X15	X16	X17	X18	X19	X20
Homework Time (X11)	1.000									
Extra Tutorial (X12)	0.221	1.000								
Word Problems-2 (X13)	0.100	0.042	1.000							
Memorize Rules-2 (X14)	0.066	0.027	0.327	1.000						
Estimate Answers-2 (X15)	0.031	0.005	0.290	0.599	1.000					
Check Answers-2 (X16)	0.160	0.079	0.276	0.317	0.279	1.000				
Math Achievement (X17)	0.124	0.094	0.142	0.082	0.023	0.075	1.000			
Parental Support (X18)	0.104	0.066	0.186	0.200	0.182	0.183	0.051	1.000		
Parents' Occupation (X19)	0.091	0.023	0.017	0.020	0.003	0.046	0.284	0.184	1.000	
Parents' Education (X20)	0.089	0.033	0.054	0.062	0.029	0.047	0.330	0.246	0.543	1.000

Note: Coefficients > .062 are significant at $p < .05$

In the structural equation approach, attempts are made to fit the variance-covariance matrix implied by the theoretical model to the variance-covariance matrix of the sample data. The estimation of the asymptomatic variance-covariance matrix needed for the WLS solution required the use of listwise selection of cases (i.e., a case with any missing data was elimitaed). The final model, therefore, included 3,101 individuals with complete data from the SIMS data file.

Results

The results of the model test are presented in the following section. Because is was decided a priori how the observed and latent variables relate to mathematics outcome, the first interest is in the assessment of fit of the hypothesized model to the data. After the fit of the model is determined to be at least adequate, the importance of the parmeter estimates can then be more clearly assessed. Without an adequate fit, the hypothesized model would need to be reconceptualized.

Six goodness-of-fit indices were used to describe the fit of the model to the data. These are presented in Table 3. The coefficient of determination for the measurement model is .94, indicating a strong relation between the observed variables and the latent variables included in the model. Coefficient of determination may be considered a measure of the reliability for the whole measurement model, showing how well the observed variables jointly serve as instruments for measuring the latent variables. Furthermore, the ability to confirm the proposed set of relations also provides evidence of the construct validity of the measurement model.

TABLE 3

Goodness-of-Fit Indices

Index	Value
Coefficient of determination	.94
Goodness-of-fit index (GFI)	.98
Adjusted goodness-of-fit index (AGFI)	.92
Root mean square residual (RMR)	.08
Chi square:degrees of freedom	2.9:1
Hoelter's critical N	221

The results indicated that the observed variables measure the latent variables well. The observed parameter estimates for each latent variable were as follows (reference observed variables were fixed at 1.00): home environment (parental support = 1.00, parents' occupation = .75; parents' education = .72); motivation (self-concept = 1.00; perseverance = .39); mathematics ability (prior mathematics achievement = 1.00); initial attitude towards mathematics (solve word problems = 1.00; memorize rules and formulas = .41; estimate answers = .40; check answers = .45); instructional time (homework time = 1.00; mathematics insrtuction time = .50); quality of instruction (learning opportunity = 1.00; study aids = .42); attitude towards mathematics (solve word problems = 1.00; memorize rules and formulas = .57; estimate answers = .53; check answers = .43); mathematics achievemebt (final mathematics achievement = 1.00). In addition, the significance of the size of the parameter estimates (the ratio of the estimate to its standard error) were tested with t tests, and all were found to be significant ($p < .05$).

Assessment of the model fit were also determined by the goodness-of-fit index (GFI) and the adjusted goodness-of-fit index (AGFI). For a good model fit, the GFI and AGFI should be close to or above .90. For the present model, the GFI was .98, and the AGFI was .92, indicating a reasonably good model fit. The GFI is a measure of the relative amount of the variances and covariances in the data accounted for by the hypothesized model. The AGFI adjusts for the degrees of freedom of a model relative to the number of variables. On the other hand, the root mean residual (RMR) is a measure of the average unexplained variances and covariances in the model. For a good model fit, the RMR should be near zero. In the present model, the RMR was .08, suggesting that few of the average variances and covariances were left unaccounted for by the model.

Another index of overall model fit is the ratio of chi square to its degrees of freedom. There is no consensus on what represents a good fit, with recommendations ranging from 3, 2, or less (Carmines and MacIver, 1981) to as high as 5 (Wheaton et al., 1977). In the present study, it is 2.9, an indication of good fit. However, problems have been reported with chi-square as a sole criterion of fit (Bentler & Bonett, 1980; Byrne & Shavelson, 1987; Cabrera et al., 1992; Long, 1983). Problems such as these led Jöreskog and Sörbom (1989) to state that the decision to accept or reject a model cannot be made on a purely statistical basis. As an alternative to the chi-square, Hoelter (1983) proposed a Critical N (CN) statistic, which an estimate of the size a sample must reach in order to accept the fit of a given model on a statistical basis. Hoelter suggests a tentative cutoff value CN $\geq$ 200 as indication that that a particular model adequately reproduces an observed covariance structure. For the present model, the va' e was 221, indicating a good model fit.

Given the variety of tests utilized to judge the adequacy of the model, it can be seen that the model fitted the data reasonably well. In investigating these, it was chosen to follow Marsh, Bella, and McDonald's (1988) recommendation that improvement in model fit should be motivated by substantive as opposed to purely statistical concerns. Although better-fitting models could be developed, the results might make little sense substantively.

<u>Factors Influencing Mathematics Outcome</u>

Because the model fits the data adequately, the validation of the model is now more able to be assessed. The goals of the present study were to identify the important productivity factors in accounting for mathematics outcome (achievement and attitude) and to determine how well the variables in the model accounted for variance in mathematics outcome as well as the latent variables in the model.

<u>Effects on Mathematics Achievement</u>. Table 4 presents a summary of direct, indirect, and total effects. The significance of the size of the effects in the model was tested through *t*-tests (the ratio of the estimate to its standard error). Those effects greater than .10 in Table 4 were significant at .05 alpha level. All of the six factors posited in Figure 1 to have direct effects on mathematics achievement have the hypothesized sign but only mathematics ability and instructional time were significant (see Figure 2). The strongest direct effect on mathematics achievement was mathematics ability (β = .72). Instructional time was weakly but significantly related to mathematics

TABLE 4

Total, Direct, and Indirect Effects of Productivity Factors on Mathematics Achievement and Attitude

Construct	Direct effect	Indirect effect	Total effect	r^1 of individual variables for structural equations
		Mathematics Achievement		
Home environment	.01	.59*	.60*	.30
Motivation	.03	.30*	.33*	.23
Mathematics ability	.72*	.15*	.87*	–
Initial attitude	–	–	–	.28
Classroom Environment	.04	.09	.13*	–
Instructional Time	.15*	–	.15*	.12
Quality of instruction	.05	–	.05	.10
		Attitude toward mathematics		
Home environment	–	.31*	.31*	
Motivation	–	.29*	.29*	
Mathematics ability	–	.12*	.12*	
Initial attitude	.63*	–	.63*	
Classroom environment	–	.02	.02	
Instructional time	.54*	–	.54*	
Quality of instruction	.07	–	.07	

*$p < .05$

achievement (β = .15). With the other productivity factors controlled, home environment, motivation, classroom environment, and quality of instruction have negligible effects, though positively, on mathematics achievement. The variables in the model structurally linked to instructional time account for only 12% of the variance, with 88% due to other factors not measured in the model (see r^2 column in Table 4). Similarly, only 10% of the variance in quality of instruction was accounted for by the variables, with 90% due to other variables not in the model.

As expected, home environment, motivation, and mathematics ability have significant indirect effect on mathematics achievement. Classroom environment had a negligible effect on mathematics achievement though in the hypothesized direction. The indirect effect home environment had on mathematics achievement (β = .47) was primarily through mathematics ability (β = .31 or .43 × .72). The most important path from home environment to mathematics achievement was through instructional time (β =.12 or .17 × .63). Home environment also influenced mathematics achievement through mathematics ability and instructional time (β = .06 or .43 × .22 × .63). Similarly, home environment influenced mathematics achievement through motivation and mathematics ability (β = .05 or .21 × .34 × .14). Additionally, home environment influenced mathematics achievement through classroom environment and instructional time (β = .03 or .32 × .14 × .63). The paths from home environment to mathematics achievement through motivation, mathematics ability, and instructional time (β = .02 or .21 × .34 × .22 × .63) through mathematics ability, classroom enviroment, and

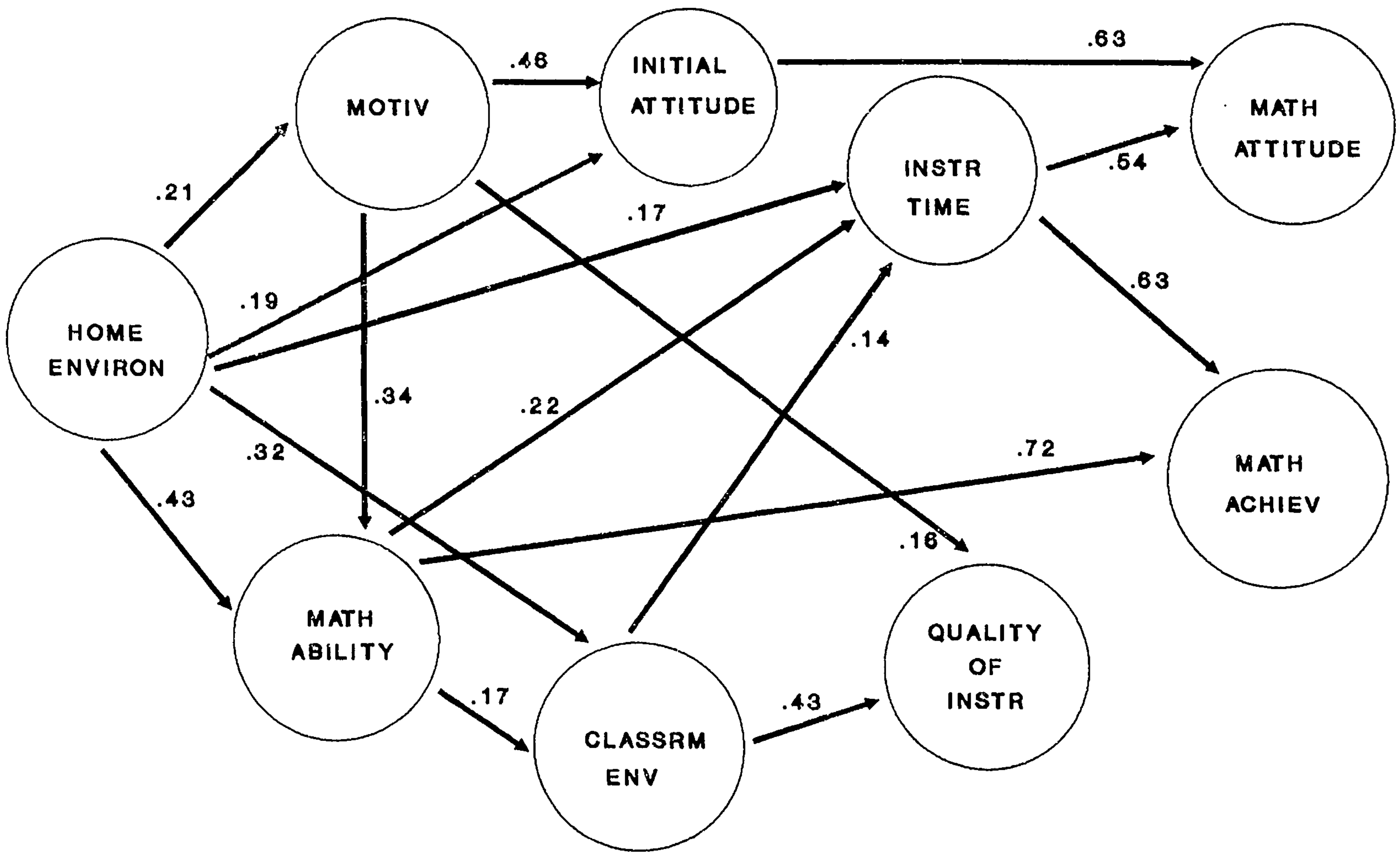

Figure 2. Significant paths ($t > 2.0$, $p < .05$)

instructional time (β = .01 or .43 × .17 × .14 × .63) were equally important. These tend to suggest that the home environment, and specifically the parents, influence children's adjuctment acnd commitment toward school, which lead to higher mathematics achievement. The variables in the model account for 30% of the variance in home environment, with 70% due to other variables not measured within the model (see r^2 column in Table 4).

Motivation also has a significant indirect effect on mathematics achievement, primarily through mathematics ability (β = .24 or .34 × .72). Motivation also influenced mathematics achievement through mathematics ability and instructional time (β = .05 or .34 × .22 × .63) suggesting that motivation can influence more student participation in academic activities, which in turn result in higher achievement. The variables in the model structurally linked to motivation account for 23% of the variance, with 77% due to other factors not measured in the model (see r^2 column in Table 4).

It was not surprising that mathematics ability had a significant indirect effect on mathematics achievement. Though it had the largest direct effect on mathematics achievement (β = .72) it also influenced more participation in mathematics learning (β = .14 or .22 × .63) as well as filtering its influence through classroom environment and istructional tim (β = .01 or .17 × .14 × .63) suggesting that able students will spend more time on school work and would adjust better to the classroom environment, all of which are precursors to high achievement.

The small indirect effect of classroom environment was not unexpected because of the increasing alienation of mathematics classrooms by students, suggesting that classroom environment may not be a good influencer of mathematics achievement. Nevertheless, classroom environemnt had a weak but significant positive total effect on mathematics achievement.

<u>Attitude Toward Mathematics</u>. Only two of the three factors posited in Figure 1 to have direct effects on attitude toward mathematics were significant (see Figure 2). The strongest direct effect on attitude toward mathematics--direct and total effects are equal if no other paths exist between the two variables--was initial attitude toward mathematics (β = .63). Instructional time was also significantly related to attitude towards mathematics (β = .54). Unexpected was the negligible effect of quality of instruction (β = .05), suggesting that the variables employed in this study were not good representations of quality of instruction (r^2 = .10). The variables in the model structurally linked to initial attitude toward mathematics for 28% of the variance, with 72% due to other factors not measured in the model (see r^2 column in Table 4).

Though they had no direct effect of attitude toward mathematics, home environment, motivation, and mathematics ability had significant indirect effect of attitude, suggesting that earlier aptitudes of students and influence of parents have a lot to do with the type of attitude students develop toward mathematics. It is interesting to note that these indirect effects tailored those on mathematics achievement and in the same other--home environment, motivation, and mathematics ability (in increasing other of magnitude)--suggesting that the development attitude toward mathematics in eighth grade are dependent on productivity factors.

Home environment (ß = .31) and motivation (ß = .29) had by far the greatest indirect effects on attitude toward mathematics, primarily through initial attitude toward mathematics. Home environmental influence also interacted with motivation and initial attitude toward mathematics (ß = .06 or .21 × .46 × .63) and with instructional time (ß = .09 or .17 × .54), suggesting the transmission of parental influence and individual persistence to attitude, even in middle school. Classroom environment had negligible indirect effect on attitude toward mathematics, suggesting that the variable: "I usually understand math class" may not be a reliable measure of classroom environment.

Although the structural relations in the model do not account for much variance in home environment, motivation, initial attitude toward mathematics, instructional time, or quality of instruction (30%, 23%, 28%, 12%, and 10% respectively), they account for 73% of the variance in mathematics outcome, with only 27% due to variables not included in the model.

Discussion

In this study, I applied the LISREL method of structural modeling to estimate and test the validity of the productivity model. It appears that structural equation modeling can make a significant contribution to research concerning the interrelations between productivity factors and mathematics outcome--especially, where theoretical mapping has been problematic.

The overall fit of the model tested in this study lends support to the assertion that mathematics outcome of eighth grade students are influenced by productivity factors. The latent constructs (with the exception of initial attitude toward mathematics) all exert direct on mathematics achievement. Initial attitude was not hypothesized to influence mathematics achievement. Most important, mathematics ability and instructional time, consistent with previous findings, appears to be both pervasive and persistent. All hypothesized latent effects have indirect effect on mathematics achievement. The negligible direct and indirect effects of classroom environment on mathematics achievement are consistent with previous findings. Previous research, however, has offered little consensus as to the reasons why.

The results of this study indicated that attitude toward mathematics can be reliably assessed as mathematics outcome. The findings suggested that eighth grade students' mathematics attitude development is similar to student gains in mathematics achievement.

The significant indirect and total effects of home environment on mathematics achievement and attitude confirms the important role parents can play in the education of their childre . The home environment influences students to improve upon their their initial mathematics ability to perform well in mathematics. Home environment also bolsters one's ego to raise their views of themselves and their ability. A stimulating home also provides one an appropriate study place and time. Parents who go through their children's homework with them tend to send a message to the children that they care and that school is important. Home environmental influence on classroom environment is an indication that the home and school should work together to help the child in school work. A child from an unconcerned and impoverished home arrives at the school door unprepared. There is very little the school can do alone to help this child without the help of the parents.

Instructional time was a significant direct influencer of both mathematics achievement and attitude. This implies that students who spend more time on their homework and have more extra tutoring tend to perform well in mathematics. The results indicated that the influence of instructional time becomes stronger when the home environment, initial mathematics ability, and classroom environment act on it.

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