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Self-Regulation of Academic Motivation: Advances in Structure and Measurement

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Self-regulation of academic motivation is an under-explored aspect of self-regulation. This paper examines the structure of Self-Regulated Academic Motivation (SRAM) in the context of an overall model of Self-Regulated Learning (SRL) that also includes aspects of the self-regulation of academic cognition. In this study we first delineate key components of SRAM i.e., Mastery Self Talk, Relevance Enhancement, Situational Interest Enhancement, Performance Relative Ability Self Talk, Performance Extrinsic Self-Talk, Self Consequences and Environmental Structuring. We then test a series of Confirmatory Factor Analysis models measuring the latent components of SRAM with data from approximately 400 first year university students. Results indicate that the measure of SRAM was a valid measure of both the first and higher-order structure of SRAM, as well as being invariant across sex groups. Fit indices for all models were in excess of criterion values. We conclude that the theoretical structure we propose for SRAM is accurately operationalised by our measure with this sample. Thus, the study provides a basis upon which further testing of the theoretical SRAM model and the measure itself may be developed.

Most educational psychologists agree that effective learning requires students' to self-regulate their cognition, motivation and behaviour (Zimmerman, 1989). Despite the importance of all three aspects of self-regulation, most research into self-regulation has focused on the nature and function of the cognitive and meta-cognitive strategies self-regulated learners use to acquire, integrate, and retrieve information (Hong, 1995; Zimmerman & Martinez-Pons, 1988). Unfortunately, however, students' ability to regulate their motivation has not received the same level of attention. As a result, there are still many unanswered questions and unresolved issues pertaining to the Self-Regulation of Academic Motivation (SRAM). Wolters (2003) suggests that one of these issues concerns the appropriate measurement of motivational regulation strategies, and the relationship of these strategies to academic achievement.

The purpose of the present research was to determine the reliability and validity of a new psychometric instrument, which was specifically developed to measure students' self-regulated academic motivation strategies. Such research is warranted for at least two important reasons. First, literature suggests that SRAM may influence the quantity and quality of students' willingness to engage and persist in academic learning (Wolters, 2003). Hence, the accurate measurement of SRAM is of interest to those (i.e., researchers and practitioners) directly concerned with extent and direction of students' motivation.

Second, recent research and theorising has suggested that students' ability to control aspects of their motivation through the use of various strategies can impact on their academic learning and achievement (Wolters, 2003). More specifically, particular dimensions of SRAM may be associated with academic achievement. These dimensions include: Mastery Self Talk, Relevance Enhancement, Situational Interest Enhancement, Performance Relative Ability Self Talk, Performance Extrinsic Self-Talk, Self Consequences and Environmental Structuring. Because these specified dimensions may differentially impact upon students' learning and achievement, it would be advantageous to have an instrument available which accurately measured these different dimensions of SRAM. At the same time it may also important to demonstrate that these different dimensions of SRAM actually formed part of an overarching construct implicating students' self-regulation of academic motivation.

Sex Differences in Students' SRAM

Recent studies have investigated sex differences in patterns of students' learning and achievement, and have attempted to determine how these may be related to students' differing motivational and strategic orientations (e.g. Bouffard, Boisvert, Vezeau, & Larouche, 1995; Meece & Holt, 1993; Wentzel, 1991). Despite this research, the literature is not unanimous either that, or how, sex differences may influence students' motivation, cognition, and achievement. (e.g. Ford, 1992; Meece & Jones, 1996; Midgely, Arunkumar, & Urdan, 1996). For these reasons, it is important to determine whether any instrument measuring students' SRAM is equally valid with females and males. It may be, for example, that females and males interpret items relating to motivation and/or strategies differentially. This, in turn, may influence the inter-sex validity of any instrument measuring these constructs.

Objectives

The specific objectives of the present study were to:

(a) outline the development of an instrument designed to measure a number of dimensions of SRAM..
(b) determine the overall psychometric properties of this instrument, with specific reference to its validity and reliability,
(c) determine the structure of SRAM, particularly whether SRAM may be a multi-dimensional and hierarchically arranged construct, and
(d) determine whether, and if so how, different dimensions of SRAM are related to students' academic achievement.
(e) determine whether the instrument is equally valid (factorally invariant) with females and males.

Instrument Development

The 35 item Self-Regulation of Academic Motivation Survey (SRAM-S) was designed to measure the following dimensions of self-regulated motivation: Mastery Self Talk (6 items), Relevance Enhancement (6 items), Situational Interest Enhancement (5 items), Performance Relative Ability Self Talk (4 items), Performance Extrinsic Self-Talk (5 items), Self Consequences (5 items) and Environmental Structuring (4 items). As indicated above, components measured by the SRAM survey corresponded to those identified in previous qualitative studies by Wolters (2003). A definition of each of these dimensions, the items measuring these dimensions, and the alpha reliabilities of these items is included in Table 1.

Paper Presented at the AARE Annual Conference, Parramatta 2005
Australian Association for Research in Education

Method

Participants

Participants in the study were 383 first year university students. 215 (54%) of these students were females, and 168 (42%) were males, with the mean age of all students being 18.5 years. Most students 302 (76%) were from Anglo-American backgrounds with Hispanics and American Indians (5% each) comprising the largest minority groups.

Procedures

A five point Likert type scale was constructed for each of the 35 items with '1' meaning 'strongly disagree', '2' meaning 'disagree', '3' meaning 'not sure', '4' meaning 'agree', and '5' meaning 'strongly agree'. The SRAM-S was administered to participants in class groups.

Overview of the Confirmatory Factor Analysis Approach

Confirmatory Factor Analyses (CFAs) assess item and scale validity by determining the extent to which variations in, and between, observed indicators (items) are 'caused' by underlying constructs. CFAs allow the researcher to specify not only how many factors are measured by a given set of items but, also, what items 'load' on which factors (Fleishman & Benson, 1987).

The specific degree to which variation in and between the indicator variables can be explained by the latent constructs is known as the measurement model's 'fit'. The first step in establishing the fit of a model is to examine the model's estimated parameters. The parameters of a model include:

(a) factor loadings (relationships between items and factors),
(b) factor correlations (relationships between factors and factors),
(c) squared multiple correlations (the amount of variance associated with each item which may be attributed to underlying factors), and
(d) error variances or uniquenesses (the amount of variance associated with each item not explained by underlying factors).

The values for each of these parameters should be permissible i.e., there should be no impossible values such as negative item or factor variances.

Once the plausibility of the model's parameters has been established, overall measures of model fit may be used. The most common measure of a model's overall fit is the Chi-square (χ^2) test. This test computes a value for the ratio of the Chi-square statistic for a given model to the degrees of freedom associated with that model (Marsh, Balla, & Hau, 1996, Mueller, 1996; Pedhazur & Pedhazur Schmelkin, 1991). If this ratio is considered small (typically less than two) then the model is deemed to 'fit' (which means *only* that the data in the present sample are not sufficient to reject the model). If the Chi-square/degrees of freedom ratio is considered large (typically greater than two) the model is deemed not to fit well (which means that the data in the present sample *are* sufficient to reject the model).

The probability associated with the Chi-square/degrees of freedom ratio also acts as a standard by which the size of the ratio may be assessed (Pedhazur & Pedhazur Schmelkin, 1991; Hayduk, 1987). However, a major difficulty with this probability statistic is that it is sensitive to increases in sample-size (Marsh, Balla, & McDonald, 1988). This means that, as the sample size in a study increases, small Chi-

Paper Presented at the AARE Annual Conference, Parramatta 2005
Australian Association for Research in Education

square/degrees of freedom ratios may yield significant probabilities *despite the fact* that models may fit the data substantially well. For this reason, the probability associated with the Chi-square test can only be used as a guide to model fit, especially where large samples are involved (Marsh, et al., 1988). This said, researchers should also be wary of disregarding probabilities associated with the Chi-square test, which, depending on their size, may still indicate poor model fit (Hayduk, 1987).

Difficulties with the Chi-square test (especially with large samples) have led researchers to develop other methods for assessing model fit (Bandalos & Benson, 1990; Marsh et al., 1996). These methods involve the use of a variety of goodness-of-fit indices. Goodness-of-fit indices are used to assess how closely a covariance or correlation matrix (a matrix of numerical relationships between items), reproduced from a hypothesised model, matches a matrix generated from actual data. If the two matrices are consistent with one another, then the goodness-of-fit indices will be large (close to one) and the hypothesised model can be considered a plausible explanation for the data.

There is considerable debate in the literature as to which of these indices are appropriate for measuring model fit and in which situations (Marsh, et al, 1988; Mueller, 1996; Pedhazur & Pedhazur Schmelkin, 1991). Despite this disagreement as to relative value of various goodness-of-fit indices, however, there is a general consensus that more than one of these indices of overall model fit should be used to evaluate a given model. The goodness-of-fit of the models tested in this research was assessed using representative indices from three broad families of fit measures, i.e., measures based on comparative fit to a baseline model, measures based on errors of approximation, and measures based on cross-validation adequacy (Kaplan, 2000; see also Marsh et al., and Marsh et al., 1988). As representatives of the first family we chose the Tucker-Lewis Index (TLI) and the Comparative Fit Index (CFI). As a representative of the second family we chose the Root Mean Square Error of Approximation (RMSEA), and as a representative of the third family we chose the Akaike Information Criteria (AIC).

<u>Higher Order Confirmatory Factor Analyses (HCFAs).</u>

First-order CFAs seek to ascertain whether various combinations of <u>items</u> may measure the same underlying construct or factor. In a similar way, HCFAs seek to ascertain whether various combinations of first-order factors may measure higher-order factors. There are two distinct advantages in identifying higher-order factors, if they exist. The first is that models may be simplified by their inclusion i.e. a smaller number of higher-order factors may be shown to account for variations in, and between, individual items and first-order factors (Lance, Teachout, & Donnelly, 1992). The second is that the inclusion of higher order factors enables researchers to identify hierarchical relations between first-order factors (Marsh & Hocevar, 1985). If these hierarchical relations conform to relations predicted from theory, the theoretical substance of models is enhanced. One distinct disadvantage, however, of models incorporating higher-order factors is that they may explain less variance in the data than first-order models. A criterion for evaluating the usefulness of higher-order models, then, is the extent to which the advantages gained from model simplification are balanced by the losses incurred in the explanatory power of these models (Lance, et al, 1992).

The HCFA reported in this study hypothesised that the seven self-regulatory motivational strategies (Mastery Self Talk, Relevance Enhancement, Situational Interest Enhancement, Performance Relative Ability Self Talk, Performance Extrinsic Self-Talk, Self Consequences and Environmental Structuring) would 'load' on a single second-order factor - Self-Regulation of Academic Motivation (SRAM).

Tests of Factorial Invariance.

When parallel data exists for more than one group, invariance tests using a CFA approach provide a way of assessing the equivalence of solutions across multiple groups (Marsh, 1994, 1993, Marsh & Hocevar, 1985). Through invariance tests, the researcher constrains any one, any set, or all parameters to be equal across multiple groups. The evaluation of models with invariance constraints involves comparing a model with no constraints against a model with constraints to determine the relative goodness-of-fit of the constrained model. The minimal condition for factorial invariance is the equivalence of factor loadings across multiple groups. Invariance analyses should be conducted with covariance matrices (not correlation matrices, which are standardised in relation to separate groups rather than multiple groups) (Joreskog & Sorbom, 1984). The present investigation tests the invariance of factor structures between males and females to establish whether these structures are, at least minimally, invariant across sex groups.

Overview of Models Tested in the Present Research

This section provides an overview of the models tested in the present research. Model 1 (M1) is a first-order model that tests the hypothesised structure of SRAM i.e., the presence of seven distinct factors corresponding to the dimensions of SRAM. Model 2 to Model 5 test the invariance of the first-order model across sex groups. Model 6 (M6) tests the hypotheses that the first order factors are nested under a higher-order factor, which constitutes the hierarchical structure of SRAM. Model 7 (M7) tests the hypotheses that the dimensions of SRAM (the first-order factors) will make differential contributions to academic achievement.

CFA Procedures

In each of the models all items were specified to load on only one factor, and the uniqueness of each item was modelled to be independent of the uniquenesses of all other items. The factor correlations were freely estimated in the first-order model, and constrained to zero in the higher-order model. Various combinations of factor loadings, factor correlations, and item uniqueness were held to be constant across groups in the tests of invariance.

All analyses were conducted using LISREL V8.54, and all parameters were estimated using the maximum likelihood procedure. An underlying assumption of maximum likelihood estimation procedures is that responses are normally distributed (Hu, Bentler & Kano, 1992). As is common in psychometric research, however, responses to the SRAM-S were not normally distributed. (In general, item responses were negatively skewed and moderately leptokurtic). Fortunately, however, maximum likelihood estimation procedures appear to be robust with respect to violations of normality, particularly in relation to parameter estimates and goodness-of-fit indices (Hu, Bentler & Kano, 1992; Joreskog & Sorbom, 1993; Muthen & Kaplan, 1985). In fact, to the extent that estimation problems are associated with non-normality, parameter estimates and observed goodness-of-fit measures tend to indicate a poorer fit if data are non-normally distributed (Hau & Marsh, 2000). For this reason, non-normality does not appear to be a significant problem with respect to maximum likelihood estimation procedures.

Paper Presented at the AARE Annual Conference, Parramatta 2005
Australian Association for Research in Education

Results

Reliabilities

Reliabilities for each of the SRAM-S scales are reported in Table 1. In general reliabilities for the scales are substantial, with all reliabilities greater than .70, and all reliabilities but one greater than .80.

Tests of the Factor Structure of SRAM

Overall results for the goodness of fit of each of the tested models are presented in Table 2. The results in Table 2 indicate that all models fit the data well. Thus, the first-order structure, higher-order structure (see Figure 1) and, to lesser extent, invariance of the first-order structure across sex groups are all supported by the data. The invariance models are, however, not an unambiguously good fit for the data, with only the TLI in models M4 and M5 reaching the generally accepted criterion level (0.90). This suggests that the models are not strictly invariant across sex groups. This finding does not undermine the integrity of the model with the sample as a whole (Model 1 held well with the whole sample). However, it does suggest that males and females may have responded to the SRAM-S in somewhat different ways.

Test of SRAM and Academic Achievement

The model (M7) testing the relationship of the dimensions of SRAM to academic achievement fit the data well (see Table 2). As hypothesised, different dimensions of SRAM were more of less strongly related to academic achievement (see Figure 2). For example, Performance Relative Ability Self Talk (explaining about 6% of the variance in academic achievement), Performance Extrinsic Self-Talk (explaining about 18% of the variance in academic achievement), were clearly most strongly associated with academic achievement. However, Mastery Self Talk (less than 3% of the variance in academic achievement), Relevance Enhancement (less than 2%), and Situational Interest Enhancement (less than .05%) were clearly less strongly (even if still statistically significantly) related to academic achievement.

Discussion

Several important features of the SRAM-S emerge from the results reported above. First, the analyses support the factorial validity of the first-order structure of the SRAM-S. This finding is important because it demonstrates that students' SRAM is not a unitary construct. Rather SRAM is multidimensional. One important implication of this multidimensionality is that SRAM may implicate quite complex psychological processes. In any given situation, for example, adept students may choose from a range of strategies to regulate their motivation. Moreover, adept students may choose appropriate combinations of strategies to address the challenges of given academic situations, and may change their use of individual or combined strategies over times and across subject domains as necessary. Conversely, less adept students may only be able or willing to access one or two strategies, which may be more or less effective in given situations. One advantage for teachers with respect to the multidimensionality of SRAM is that teachers attempting to instruct students to regulate their motivation can introduce students to a range of strategies, from which students can choose strategies which suit them.

Paper Presented at the AARE Annual Conference, Parramatta 2005
Australian Association for Research in Education

Table 1
Strategies Measured by the SRAM-S

Construct (Strategy)	SRAM-S Items	Alpha
	Mastery Self-Talk (MST)	
MST Refers to students' use of thoughts or sub vocal statements to encourage themselves to demonstrate understanding, academic competence, or improved performance relative to self-established standards.	1. I convince myself to work hard just for the sake of learning 2. I tell myself that I should study just to learn as much as I can 3. I think about trying to become good at what we are learning or doing 4. I tell myself that I should keep working just to learn as much as I can 5. I persuade myself to keep at it just to see how much I can learn 6. I challenge myself to complete class work and learn as much as possible	.867

Paper Presented at the AARE Annual Conference, Parramatta 2005
Australian Association for Research in Education

	Relevance Enhancement (RE)	.867
RE Refers to cognitive self-talk and other self-coaching strategies intended to make academic material more relevant or meaningful e.g., students may identify and focus on the material's personal relevance and/or the material's utility value.	7. I tell myself that it is important to learn class material because I will need it later in life. 8. I try to connect class material with something I like doing or find interesting. 9. I think up situations where it would be helpful for me to know class material or skills. 10. I try to make class material seem more useful by relating it to what I want to do in my life. 11. I try to make myself see how knowing class material is personally relevant. 12. I make an effort to relate what we're learning to my personal interests.	
	Situational Interest Enhancement (SI)	
SI Refers to self-coaching strategies designed to increase the immediate enjoyment of an academic activity or increase the situational interest students experience while completing an activity.	13. I try to make a game out of learning class material or completing an assignment 14. I try to get myself to see how doing class work can be fun 15. I make doing class work enjoyable by focusing on something about it that is fun 16. I think of a way to make class work seem enjoyable to complete 17. I make studying more enjoyable by turning it into a game.	.858
	Performance Relative Ability Self-Talk (PST)	
PST Refers to self-coaching strategies designed to focus students' attention on various performance-relative ability reasons for	18. I think about doing better than other students in my class 19. I tell myself that I should work at least as hard as other students. 20. I keep telling myself that I want to do better than others in my class	.842

Paper Presented at the AARE Annual Conference, Parramatta 2005
Australian Association for Research in Education

wanting to complete an activity e.g., when faced with an urge to quit studying a student may purposefully think about doing better than others as a way of convincing themselves to continue working.	21. I make myself work harder by comparing what I'm doing to what other students are doing	
	Performance Extrinsic Self-Talk (EST)	
EST Refers to a focus on various performance-extrinsic-related reasons for wanting to complete an activity e.g., when faced with an urge to quit studying a student may purposefully think about getting high grades as a way of convincing themselves to continue working.	22. I convince myself to keep working by thinking about getting good grades 23. I think about how my grade will be affected if I don't do my reading or studying 24. I remind myself how important it is to do well on tests and assignments in my classes 25. I remind myself about how important it is to get good grades 26. I tell myself that I need to keep studying to do well in my classes	.843
	Self Consequences (SC)	
SC Refers to self-coaching strategies designed to identify and administer extrinsic reinforcements for reaching particular goals associated with completing a task.	27. I promise myself I can do something I want later if I finish assigned class work now 28. I make a deal with myself that I can do something fun after I get a certain amount of work done 29. I promise myself some kind of a reward if I get my readings or studying done 30. I tell myself I can do something I like later if right now I do the work I have to get done 31. I set a goal for how much I need to study and promise myself a reward if I reach that goal	.915

Australian Association for Research in Education
Paper Presented at the AARE Annual Conference, Parramatta 2005

	Environmental Structuring (ENS)	
ENS Refers to strategies designed to decrease the possibility of off task behaviour by reducing the probability of encountering a distraction or by reducing the intensity of distractions that do occur.	32. I make sure I have as few distractions as possible 33. I try to get rid of any distractions that are around me 34. I eat or drink something to make myself more awake and prepared to work 35. I change my surroundings so that it is easy to concentrate on class work	.750

Paper Presented at the AARE Annual Conference, Parramatta 2005
Australian Association for Research in Education

Table 2
Model Fit Statistics for SRAM-S

Model	χ^2	df	χ^2/df	TLI	CFI	RMSEA	AIC	Model Description
M1	1387.85	539	2.57	.97	.98	0.6	1569.85	First Order Model
M2	4592.80	1169	3.93	.89	.89	0.10	4774.80	Totally Invariant
M3	4484.60	1141	3.93	.89	.89	0.10	4722.60	FL and U invariant
M4	4341.36	1134	3.82	.89	.90	0.10	4593.36	FL and FC invariant
M5	4267.63	1106	3.86	.89	.90	0.10	4575.63	FL invariant
M6	1600.25	553	2.89	.97	.97	.070	1754.25	Higher Order Model
M7	3562.17	588	6.06	.93	.94	.110	1694.36	SRAM-Achievement

Note:
TLI = Tucker-Lewis Index; PRNI = Parsimony Relative Noncentrality Index; RMSEA = Root Mean Square Error of Approximation. A null model is a model in which no factor structure is estimated. The null model is used as a basis of comparison with a hypothesised model (a model in which an a-priori factor structure is estimated) in both the TLI and the PRNI.

TLI = [Chi-square/degrees of freedom (null model)] - [Chi-square/degrees of freedom (hypothesised model)]
Chi-square/(degrees of freedom -1) (null model)

PRNI = [Chi-square - degrees of freedom (null model)] - [Chi-square - degrees of freedom (hypothesised model)]
Chi-square - (degrees of freedom -1) (null model)

RMSEA = Square Root [(Chi-square – degrees of freedom)/(n-1)degrees of freedom]

Factor Correlation (Phi) Matrix

	MST	RE	SI	PST	EST	SC	ENS
MST	1.000						
RE	0.82	1.000					
SI	0.64	0.80	1.000				
PST	0.67	0.57	0.44	1.000			
EST	0.67	0.53	0.32	0.62	1.000		
SC	0.62	0.57	0.46	0.47	0.52	1.000	
ENS	0.63	0.52	0.41	0.42	0.66	0.53	1.000

The higher-order analysis provided empirical evidence that the multiple dimensions of SRAM are in fact nested in a single hierarchical structure. This is theoretically important because it demonstrates that the dimensions of SRAM, although distinct, are different methods of achieving the same self-regulatory objective i.e., regulation of motivation. Together, the multidimensional and hierarchical structure of the SRAM-S provides a means by which researchers can further investigate students' individual self-regulatory strategies with respect to motivation, *and* the ways these may interact and combine to influence students' achievement. The hierarchical structure of the SRAM-S may also provide researchers with a means of constructing a parsimonious model of student self-regulation of motivation, through the use of a higher-order latent factor that subsumes individual dimensions of SRAM at the first-order level.

The invariance tests were not as conclusive as the first-order and higher-order models. However, the invariance tests do provide evidence that the multidimensional structure of SRAM maybe invariant across sex groups when factor loadings and/or

Paper Presented at the AARE Annual Conference, Parramatta 2005
Australian Association for Research in Education

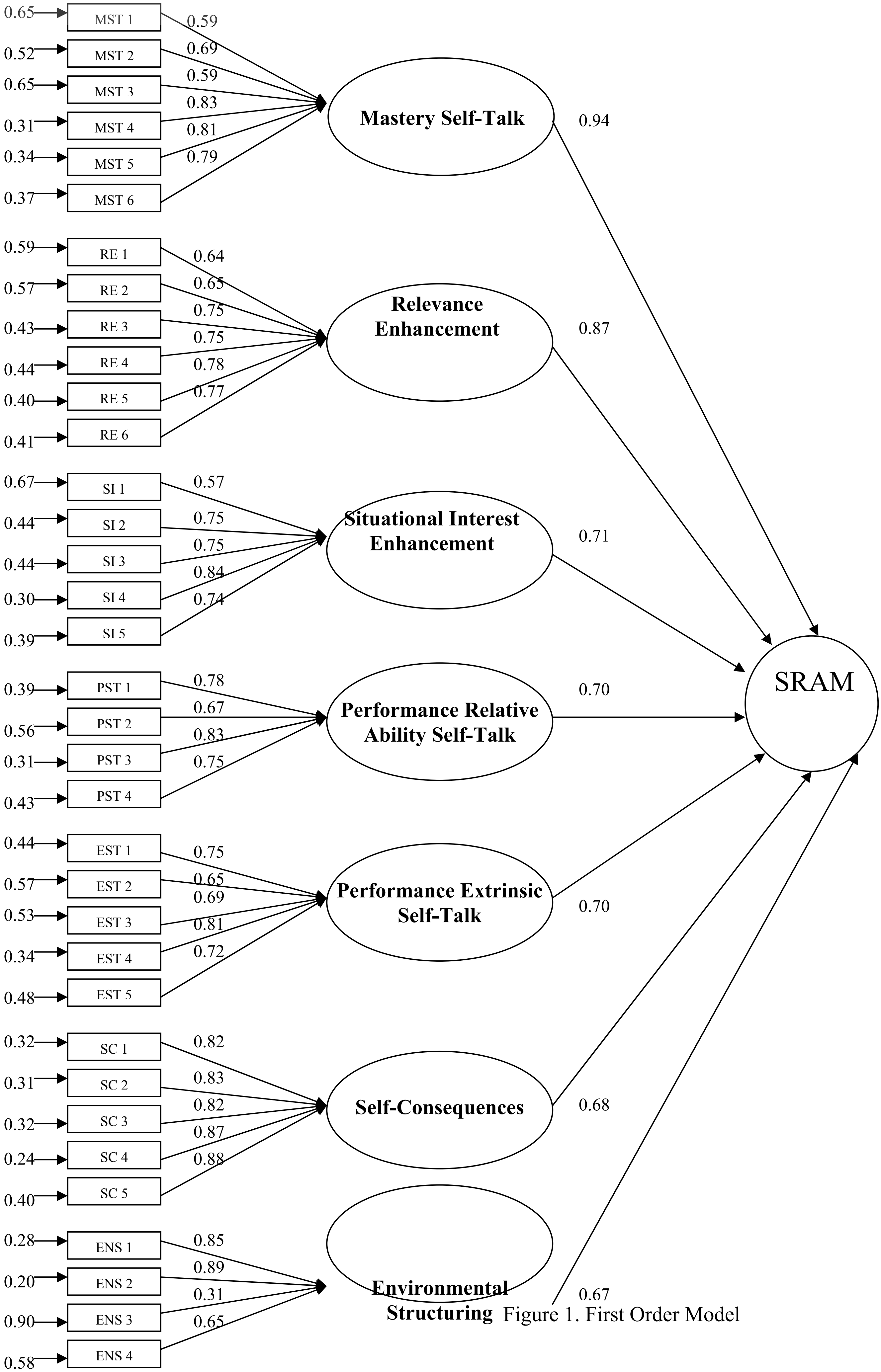

Figure 1. First Order Model

Paper Presented at the AARE Annual
Conference, Parramatta 2005
Australian Association
for Research in Education

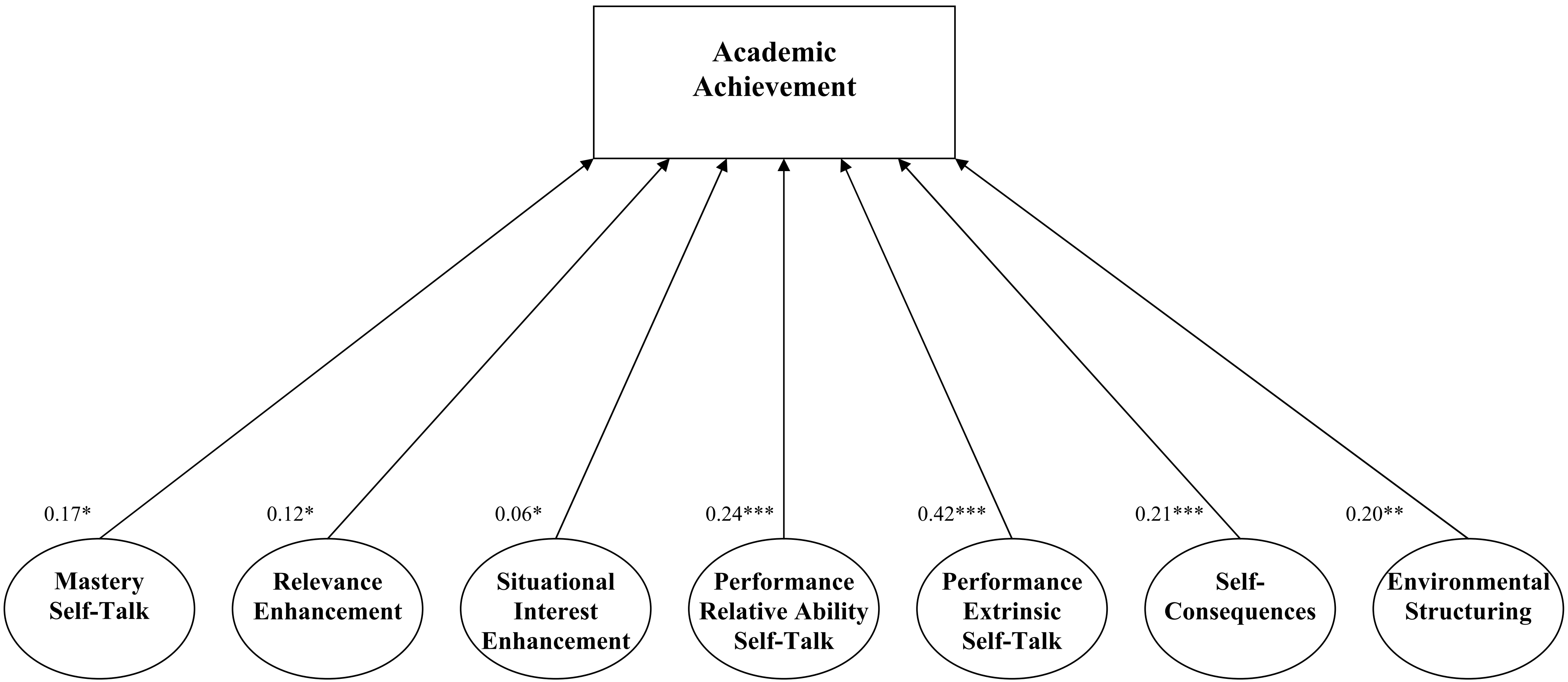

Figure 2. Higher Order Model (M7)

Paper Presented at the AARE Annual Conference, Parramatta 2005
Australian Association for Research in Education

factor correlations are held constant. Also the fact that the two invariance models with uniquenesses held invariance (i.e., the totally invariant model and the factor loadings/uniquenesses model) fit the data less well than the models without uniquenesses, suggests that the major measurement differences across sex involve the uniquenesses (error terms). Conversely, the structural elements of the models may be more stable across sex-groups. For applied researchers, these error terms are perhaps not as important as the factor loadings and correlations. Despite this observation, further studies will be necessary to better determine the factorial stability of the SRAM-S across sex-groups.

SRAM and Academic Achievement

SRAM was clearly associated with academic achievement. Together the seven SRAM factors explained 36% (approx.) of the variance in academic achievement. As predicted, however, some dimensions of SRAM were more closely associated with achievement than others. In particular, Performance Extrinsic Self-Talk, and to a lesser extent Performance Relative Ability Self Talk, Self Consequences and Environmental Restructuring; explained the majority (88% approx) of the total variance explained in academic achievement, with Performance Extrinsic Self-Talk accounting for nearly 50% of the total explained variance on its own. As is becoming clear in growing number of recent studies (e.g., Barker, Dowson, & McInerney, 2002; Dowson & McInerney, 2003), performance-type orientations and strategies are not necessarily detrimental to achievement. This research adds weight to these previous studies. One key implication of this pattern of relationships for achievement is that a focus on extrinsic rewards and ability relative to others is not necessarily detrimental to either motivation or achievement. Conversely, mastery and interest type strategies (often cited as the most appropriate strategies for student to adopt) may not be as powerful contributors to motivation achievement as preciously suggested.

Conclusion

This research provides strong support for the multi-dimensionality and hierarchical arrangement of SRAM. It also identifies that SRAM is strongly associated with higher academic achievement, particularly through the use of Performance Extrinsic Self-Talk. Finally, the study provides lesser support for the invariance of the SRAM-S across sex groups. Despite the limitations of the research, it nevertheless makes a useful and necessary contribution measurement of SRAM, and the estimation of the impacts of SRAM on academic achievement.

Paper Presented at the AARE Annual Conference, Parramatta 2005
Australian Association for Research in Education

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Paper Presented at the AARE Annual
Conference, Parramatta 2005
Australian Association
for Research in Education

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