Transforming the Future of Learning with Educational Research

Helen Askell-Williams
Flinders University, Australia

A volume in the Advances in Educational Technologies and Instructional Design (AETID) Book Series

Information Science REFERENCE
An Imprint of IGI Global

Managing Director: Lindsay Johnston
Managing Editor: Austin DeMarco
Director of Intellectual Property & Contracts: Jan Travers
Acquisitions Editor: Kayla Wolfe
Production Editor: Christina Henning
Development Editor: Allison McGinniss
Typesetter: Tucker Knerr
Cover Design: Jason Mull

Published in the United States of America by
Information Science Reference (an imprint of IGI Global)
701 E. Chocolate Avenue
Hershey PA, USA 17033
Tel: 717-533-8845
Fax: 717-533-8661
E-mail: cust@igi-global.com
Web site: http://www.igi-global.com

Library of Congress Cataloging-in-Publication Data

Transforming the future of learning with educational research / Helen Askell-Williams, editor.
pages cm
Includes bibliographical references and index.
ISBN 978-1-4666-7495-0 (hardcover) -- ISBN 978-1-4666-7496-7 (ebook) 1. Learning. 2. Learning--Research. 3. Teaching. 4. Teaching--Research. I. Askell-Williams, Helen, 1955- editor of compilation.
LB1060.T734 2015
370.15'23--dc23
2014045456

This book is published in the IGI Global book series Advances in Educational Technologies and Instructional Design (AE-TID) (ISSN: 2326-8905; eISSN: 2326-8913)

British Cataloguing in Publication Data
A Cataloguing in Publication record for this book is available from the British Library.

Chapter 1
Changes in Students' Cognitive and Metacognitive Strategy Use over Five Years of Secondary Schooling

Helen Askell-Williams
Flinders University, Australia

Michael J. Lawson
Flinders University, Australia

ABSTRACT

As students progress through school, we expect that their knowledge about the various subject matters, such as biology or maths, becomes more extensive, well structured, and readily available for application in diverse contexts. This chapter reports the authors' enquiry about whether students' cognitive and metacognitive knowledge and strategies do grow during secondary school. Questionnaires were administered to students in three South Australian secondary schools in each of five consecutive years. Hierarchical linear modelling was used to investigate changes in students' responses over time. Results showed little change in students' reports of their cognitive and metacognitive strategy use. The disappointing growth trajectories suggest that cognitive and metacognitive strategies for learning are not subject to the explicit teaching and evaluation processes applied to other school subjects. Questions are raised about whether schools and teachers value and recognise the importance of cognitive and metacognitive strategies for good quality learning across subject domains.

INTRODUCTION

A number of authors have highlighted the importance of self-regulation to support effective learning (Schraw, Crippen, & Hartley, 2006; Schunk & Zimmerman, 1989; Zimmerman, 2002). Conceptual frameworks for self-regulated learning have been formulated by authors such as Boekaerts and Corno (2005), Efklides (2011), Hadwin & Winne (2012), Schunk and Zimmerman (2013) and Sitzman and Ely (2011). Typically self-regulated learning is defined as, "the modulation of affective,

DOI: 10.4018/978-1-4666-7495-0.ch001

cognitive, and behavioral processes throughout a learning experience to reach a desired level of achievement" (Sitzman & Ely, 2011, p. 421). In Schunk and Zimmerman's model, the three major phases of self-regulation involve forethought (e.g., motivation, beliefs, task analysis, planning), performance (e.g., monitoring, self-instruction, attention, elaboration) and self-reflection (e.g., self-evaluation, attributions, affective reactions). These phases incorporate the motivational, cognitive and metacognitive components of learning discussed by Mayer (1998). Schraw et al. (2006) proposed that good self-regulators learn more with less effort, and Schwonke et al. (2013) explained that self-regulation requires learners to employ motivational, cognitive and metacognitive strategies. The focus of this chapter is upon students' cognitive and metacognitive strategies for learning.

The Beneficial Effects of Cognitive and Metacognitive Strategies

A generation ago, Weinstein and Mayer (1986) provided an overview of useful strategies to enable students to learn subjects, such as biology and maths, efficiently and effectively. Cognitive strategies can include generating questions, taking notes, making mental images, and drawing concept maps (Kiewra, 2002; Novak, 1990). Meanwhile, metacognitive knowledge (declarative, procedural, conditional) and regulation (planning, monitoring, evaluation) directs the use of cognitive strategies (Schraw et al., 2006). In other words, higher-order metacognitive processes monitor and regulate lower-order cognitive processes (Nelson, 1996). By way of example, Veenman and Veenman (2011) explained that drawing inferences is a cognitive activity, but the self-induced decision to initiate such activity is metacognitive.

Shortly following the Weinstein and Mayer (1986) overview, Klauer (1988 p. 351) argued that "teachers should be qualified not only to teach the respective subject matter but also to teach students how to learn this subject matter". Since then, a wealth of studies has demonstrated the beneficial effects of cognitive and metacognitive strategies for good quality learning. For example, Roebers, Cimeli, Röthlisberger and Neuenschwander (2012) proposed that declarative metacognitive knowledge directly and substantially influences students' academic outcomes, having been shown, for example in PISA studies, to have a long-term impact on school careers and a short term impact on test performance. Similarly, Roebers et al. argued, metacognitive monitoring and control processes account for individual differences in test performance, controlling for psychometrically tested intelligence. Hattie's (2009, pp. 297-300) meta-analysis overviewed a range of effect sizes (Cohen's *d*) for study skills instruction involving cognitive, metacognitive and affective components, revealing an average effect size of 0.59, with a higher average effect of 0.69 for metacognitive strategy instruction. Hattie argued that study skill instruction can be effective on its own for acquiring surface level information, but is more effective when embedded within the subject matter domains in order to assist with deeper levels of understanding.

The Development of Cognitive and Metacognitive Strategies

Models of the development of expertise have suggested that subject matter knowledge, and cognitive and metacognitive strategy knowledge, develop in concert with each other. For example, Alexander, Jetton and Kulikowich's (1995) model of domain expertise proposes concurrent rises in knowledge, interest and learning strategies as learners maintain their engagement with an area of study. Similarly, Chi (1985) argued that both subject-matter knowledge and strategy knowledge are essential components of developing expertise.

Van der Stel and Veenman's (2010) study of the development of early adolescents' metacognitive skills found a continuous growth of metacognitive skills with increasing age, accompanied by intellectual growth. In their study, 14 year old students performed more and better planning activities in maths than 13 year olds. In the subject of history, 14 year olds evaluated their work more frequently and at a higher level. Van der Stel and Veenman's findings are partially consistent with a review of the strategy development literature reported by Hübner, Nückles, and Renkl (2010). Hübner et al. collated research findings to indicate that high school students from ages 10 to 16 develop more sophisticated cognitive and metacognitive strategies (Pintrich & DeGroot, 1990), that 5th graders use elaborations less frequently than 12th graders (Beuhring & Kee, 1987) and similarly, that 5th graders report less use of self-regulated learning strategies than 8th graders (Zimmerman & Martinez-Pons, 1990). However, Schwonke et al. (2013) have argued that although domain knowledge has the potential to facilitate the development of metacognitive knowledge and strategies, the development of metacognition is neither an automatic nor guaranteed partner to increased domain knowledge.

A consistent message from the literature is that, notwithstanding developmental progression, some learners continue to demonstrate learning strategy deficits (e.g., Askell-Williams, Lawson, & Skrzypiec, 2012; Brown, Bransford, Ferrara, & Campione, 1983; Winne, 2005) suggesting that some students do not implicitly, vicariously, or through osmosis, absorb effective learning strategies as they grow older. Indeed, Schneider (2010) argued that memory development is not necessarily due to maturation, but rather, due to education and practice. Furthermore, a five week study that traced log files of elementary students' study strategies by Malmberg, Järvenoja and Järvelä (2013) indicated that actual use of study strategies may not be predictable based upon whether the students possess the relevant strategy knowledge. Malmberg et al. reported that students' strategic actions varied according to their ability and task difficulty. In that tracking study, whereas both high- and low-achieving students adopted similar strategies in favourable learning situations, when the learning situation was considered challenging, low-achieving students resorted to using surface-level strategies. Schwonke and colleagues' (2013) advice about the need to develop students' conditional metacognitive knowledge is particularly relevant here.

In summary, there is strong evidence from the literature about links between effective learning strategies and good quality learning. There are arguably intuitive and explicit expectations that as students mature and are exposed to more years of schooling and engagement with their subject matter, they would demonstrate increased use of effective cognitive and metacognitive strategies for learning. That is because, alongside instruction in the various subject-matter domains, students might be receiving both informal and formal instruction in, and opportunities to practise, the various cognitive and metacognitive strategies required to support their acquisition of subject-matter knowledge. However, authors such as Bransford, Brown and Cocking (2000) and Hattie (2009) have argued that the value of cognitive and metacognitive strategies is not recognised by teachers and students in many classrooms. If this is the case, expectations that students' cognitive and metacognitive strategy knowledge will grow during their schooling years may be ill-founded.

Whereas school students are regularly subjected to calibrated tests to measure growth in their subject matter knowledge (e.g., NAPLAN ACARA, 2011; PISA OECD, n.d.), tests to measure growth in other areas, such as learning strategies, are rare. In the research literature, longitudinal studies about students' cognitive and metacognitive growth usually deal with relatively short time frames, typically of a few months to a couple of years (e.g., van der Stel & Veenman, 2010). In this chapter we address this gap in the literature with a five-year study that investigates students' reported use of selected cognitive and metacognitive strategies as they progress through their secondary schooling.

Research Questions

1. Do students report increased use of good quality cognitive and metacognitive strategies for learning as they progress through secondary school?
2. Do students' reports vary by gender, school, year level and learning strategy groups?

METHOD

Sample

A questionnaire was administered to students attending three metropolitan secondary schools in Adelaide, South Australia, at the end of each academic year for five consecutive years. Two schools were rated as minimum disadvantage schools on the Departmental Index of Educational Disadvantage[1] with, respectively, 12% and 17% of students receiving school fee relief. The third school was rated as high disadvantage with approximately 79% of students receiving school fee relief. A limitation of this study is that only schools in the Adelaide metropolitan area of South Australia were included in this study.

Ethics

Ethics approvals were obtained from the Flinders University Social and Behavioural Research Ethics committee and from the South Australian Department of Education and Child Development. Agreement to conduct the study was obtained from each site manager. Consent to participate was obtained from parents and students. Participation in the study was informed, voluntary and confidential.

Questionnaire Design

For the design of the questionnaire items we reviewed previous questionnaires and checklists (such as PALS, Midgley et al., 2000; MSLQ, Pintrich & DeGroot, 1990; SEM, Schraw & Dennison, 1994). For the cognitive items, we adopted Mayer's (1998) framework of three stages of knowledge acquisition, namely, focussing attention, elaborative processing, and organising and summarising. For the metacognitive items, we adopted the conceptual categories of monitoring of knowledge, and control of thinking processes and learning activities (e.g., Pintrich, 2004). In order to keep the questionnaire relatively short, (both to fit into the time span of a regular class lesson and also to keep students' interest), we reduced the initial large item bank to 11 items (see Table 1) that represented a range of areas of cognitive and metacognitive strategy use promoted in the literature as being important. With a view to provoking students to think about a subject where they were succeeding and where their strategy knowledge

Table 1. Cognitive and metacognitive strategies items

I draw pictures or diagrams to help me understand this subject
I make up questions that I try to answer about this subject
When I am learning something new in this subject, I think back to what I already know about it
I discuss what I am doing in this subject with others
I practise things over and over until I know them well in this subject
I think about my thinking, to check if I understand the ideas in this subject
When I don't understand something in this subject I go back over it again
I make a note of things that I don't understand very well in this subject, so that I can follow them up
When I have finished an activity in this subject I look back to see how well I did
I organise my time to manage my learning in this subject
I make plans for how to do the activities in this subject

Table 2. Student sample sizes per annum

Year Level	2007	2008	2009	2010	2011
7	517				
8	421	368			
9	368	265	363		
10		223	269	317	
11			220	217	269
12				183	144
13					1
Total	1306	856	852	717	414

would be most likely to be used, students were asked to think about the subject that they "do best at", when they responded on 7-point Likert scales, (Strongly Disagree [1] to Strongly Agree [7]) to the 11 items shown.

Results

Table 2 illustrates the sampling design for the study, showing that some students contributed data to all five years of data collection, whilst other students were available for shorter periods of time.

Participant attrition occurred over the five years due to a number of factors, including administrative arrangements at the school level, students transferring between schools, and some students not completing five years of secondary schooling. A limitation of this study is the possibility that students who dropped out of the study may have different characteristics to students who remained.

Demographic Characteristics of Participants

Questionnaires were distributed in class to students who were present on the day. Therefore the response rates within each class in each year were almost 100%, with only rare students failing to submit completed questionnaires at the end of the lesson. Questionnaires with invalid responses, and consistently extreme responses (e.g., all "Strongly Agree") comprised less than 1 per cent of the sample and were discarded, leaving 4145 valid questionnaires. Approximately 9% of students reported that their parents spoke a language other than English at home. Students' ages ranged from 11 to 15 years (M = 13.4 years; SD = .94), with 49% boys, 44% girls and 7% gender not stated. The proportion of students identifying as Aboriginal or Torres Strait Islander was less than 1% in each of two schools, and approximately 9% in the third school. Students' nominations of their "best subject", designed to elicit their learning strategies in the most favourable circumstances, ranged widely. Table 3 shows the subject nominations in 2009, ranging from 1 student nominating Electronics, to 477 students nominating Health and Physical Education. Frequencies of subject nominations in the other years of data collection were similar.

Principal Components Analysis

The 11 cognitive and metacognitive questionnaire items were subjected to Principal Components Analysis (PCA) (conducted separately for each year of data collection). The correlation matrices of the items showed that most coefficients were above .2 and below .6, indicating that the items were suitable for PCA. A Learning Strategies factor was identified, accounting for 42.2% of the variance in 2007 to 50.5% of the variance in 2011, with all item weightings above .4. The Kaiser-

Table 3. Numbers of students nominating each school subject as their "best"

Subject	No.		Subject	No.
Electronics	1		Media	10
Geography	1		Craft	11
Integrated Studies	1		Biology	15
Learning Support	1		Humanities	16
Sex Education	1		Photography	17
Accounting	2		History	18
Chess Club	2		Information Technology	24
Robotics	2		Foreign languages (various)	36
Philosophy	3		Dance	52
All subjects	5		Drama	58
Legal Studies	6		Society & Environment	65
Tourism	7		Science	76
Computing	8		Food Technology	80
Physics	8		Music	91
Psychology	8		Technical studies	132
Business Studies	9		Art	237
Chemistry	9		Maths	310
Family Studies	9		English	342
			Health & Physical Educ.	477

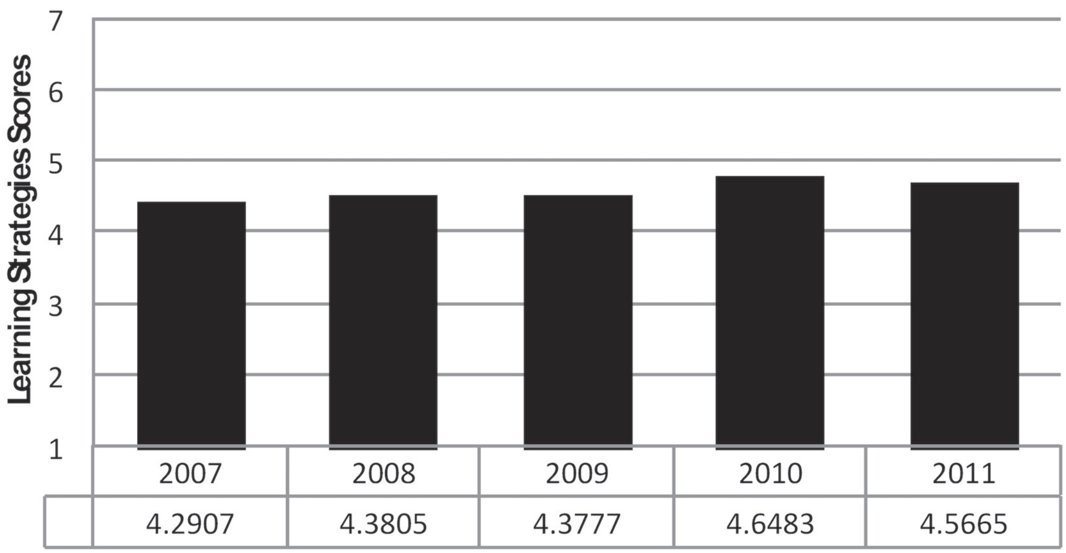
NB: Some students nominated more than one subject.

Meyer-Olkin values exceeded .9, exceeding the recommended value of .6 (Kaiser, 1970, 1974). The Bartlett Tests of Sphericity (Bartlett, 1954) reached statistical significance ($p < .0001$). Communalities ranged from .2 to .6. Scale reliabilities (Cronbach's Alpha) were above the minimum recommended value of .7 (Field, 2006).

The PCA confirmed the factor structure of the 11 items. However, the resulting factor scores, ranging from -3 to +3, showed little resemblance to the original Likert scale scores of 1: Strongly Disagree to 7: Strongly Agree, making subsequent analyses difficult to disseminate to a broader audience. Therefore, we calculated a Learning Strategies score for each student based upon each student's averaged (mean) item scores. Analyses using students' factor scores and averaged scores were substantively similar. Therefore, in order to maintain a connection with the meaning of the original Likert scales, we used students' averaged Learning Strategies scores for subsequent analyses and the results reported in this chapter.

We sorted students into four learning strategies groups based upon the students' initial (2007) Learning Strategies scores. This generated four groups, namely, low (< 1SD below mean); low-medium (1SD below mean to mean); medium-high (mean to 1SD above mean); and high: (> 1SD above mean). Next, students' Learning Strategies scores for 2008 to 2011 were corrected using the formula proposed by Nielsen, Karpatschof and Kreiner (2007) to account for potential regression to the mean that may occur when participants are categorised according to their scores on occasion one and those scores are compared to their scores in future years, as was the case in this study.

Figure 1. Mean scores of the 11 Learning Strategies scale for all students in each year of data collection 2007-2011



Descriptive Statistics

Our first research question asked whether students reported increased use of cognitive and metacognitive strategies for learning as they progress through secondary school. Figure 1 shows the mean scores of the 11-item Learning Strategies scale for all students in each year of data collection. It can be seen from this cross-sectional information that the mean scores are slightly above the mid point on the 7-point Likert scale, and show little variation over the five years. This descriptive analysis shows little differentiation, so the next step in our analysis was to use Hierarchical Linear Modelling (HLM) to investigate within-student and between-student variations over time.

The HLM Analysis

Our second research question asked whether students' reports varied by gender, school, year level and learning strategy group. To investigate this question we undertook two-level HLM (V6)[2]. HLM is capable of handling missing data, such as where students left the school, or missed a year due to illness or other reasons.

To begin, the two-level null model with no predictors using full maximum likelihood estimation was tested, as specified in Equation 1.

Equation 1: The Null Model

LEARNING STRATEGIES = P0 + E

P0 = B00 + R0

The reliability of the intercept in the null model was 0.811. The Deviance was 12802.623, which provides a baseline for comparing subsequent models containing predictors. The level 2 intercept was significant at $p = 0.000$, accounting for 63% of the variance[3], thus indicating a between student effect and confirming that multi-level modelling is appropriate for this data set. The residual level 1 variance (within student) was 37%, which also provides a point of comparison for models with more predictors.

The second, intermediate step, was to add the main predictor of interest in this study (Palardy, 2013), namely TIME, which was entered at level 1, uncentred, coded 0,1,2,3,4 for the years 2007 to 2011 respectively. Equation 2 sets out the baseline model.

Equation 2: The Baseline Model

LEARNING STRATEGIES = P0 + P1*(TIME) + E

P0 = B00 + R0

P1 = B10 + R1

The reliabilities in the intermediate model were .632 for the intercept and .128 for the slope (TIME), exceeding the minimum threshold of 0.05 (Bryk & Raudenbush, 2002). The Deviance was 12591.647, which was 210.976 less than the null model and significant at p = 0.000. The level 2 intercept continued to be significant at p = 0.000. However, the slope of TIME was not significant (p = 0.175), contradicting our expectation that as students spend more years in secondary school they would report increased use of demonstrably valuable learning strategies. However, as a finding of no significant change over time in students' reported learning strategies would be as theoretically important as a finding of significant change, we retained TIME in the next stage of the HLM analysis.

The third step in our analysis was to specify the full model, by adding predictors to the student level (level 2) of the HLM analysis. The variables were specified as follows:

Level 1: within student effects

TIME remained entered at level 1, uncentred, coded 0,1,2,3,4 for the years 2007 to 2011 respectively[4].

Level 2: between student effects

Four GROUPS of students, which were categorised according to their averaged Learning Strategies scores were represented by dummy variables, (coded 0:1), namely, low; low-medium; medium-high, with the fourth group, high, acting as the reference group.

GENDER was coded Boys 0; Girls 1.

SCHOOL was represented by dummy variables (coded 0:1), namely school A; school B, with school C acting as the reference group.

In addition, YEAR LEVEL was coded according to students' actual year level (grade) in 2007, namely, Year 7, 8 or 9, entered centred. This variable showed no significant effects on the intercept or the slope and was dropped from the full model.

The level 2 estimators of the level 1 intercept and slope were both modelled as potential random effects, as shown in Equation 3.

Equation 3: The Final Two-Level Random Coefficients Model

Level-1 Model

LEARNING STRATEGIES = P0 + P1*(TIME) + E

Level-2 Model

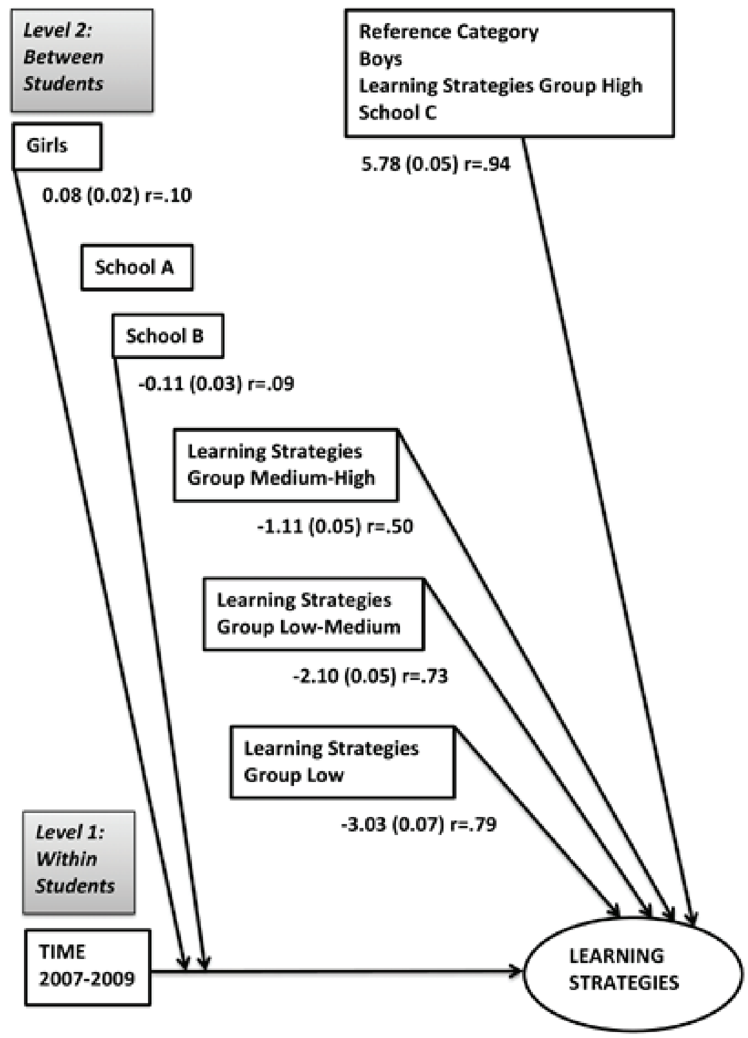
P0 = B00 + B01*(GEND) + B02*(SCH A) + B03*(SCH B) + B04*(LS-LO) + B05*(LS-LM) + B06*(LS-MH) + R0

P1 = B10 + B11*(GEND) + B12*(SCH A) + B13*(SCH B) + B14*(LS-LO) + B15*(LS-LM) + B16*(LS-MH) + R1

The final full maximum likelihood HLM analysis is displayed in Figure 2. Between student effects are modelled at level 2, and within-student effects (changes over time) are modelled at level 1.

We deal first with the diagnostic statistics associated with the full HLM analysis. The reliability estimates were 0.133 for the intercept and 0.286 for the slope (TIME). From Table 4 it can be seen

Figure 2. A visual representation of the HLM analysis



Two level hierarchical linear model with path coefficients (robust standard errors)
Effect sizes r=.1, small; r=.24 medium; r=.37, large.

that the likelihood ratio test indicated a reduction in deviance, from the null 3 parameter model to the 18 parameter final model, of 10902.858, an amount significant at p = 0.000, indicating a better fitting model. The test of homogeneity of level 1 variance was not significant, as required.

Estimates of effect sizes for the overall model were based upon reductions in level 1 and level 2 variances. The reductions in variance were calculated based upon models with random intercepts, but with the slopes fixed, in order to avoid computational difficulties associated with covariance of random effects (see Garson, 2013; Snijders & Bosker, 2012). Table 4 shows two calculations of effect sizes (R^2). The first, between the null model and the final model, and the second between the intermediate baseline model and the final model. The effect sizes are very similar, indicating that approximately 50% of the variance in the initial (null) model is accounted for by the final random intercept (only) model, which acts as an approximation of the effect size for the final model, controlling for other variables in the models. These broad estimates indicate that the addition of explanatory variables to the final model accounted for a relatively large effect between students, and a relatively much smaller effect within students (i.e., TIME).

Table 5 shows the final model, with random intercepts and random slopes. The INTERCEPT1 term is variance associated with the level 2 (between-student) effects. (Recall that in this model, each individual student is a "group" containing up to five points of data collection). The level 2 intercept, which was modelled as a function of student, gender, school and learning strategies group at level 2, has a variance component of 0.067, and in the final model no longer exerts a significant effect on the mean Learning Strategies score (the intercept). Meanwhile, the "TIME slope" term is the variance associated with random effects on the slope of time as a predictor of Learning Strategies scores. This random effect, which was modelled as a function of student, gender, school and learning strategies group at level 2, has a variance component of 0.046, and although small is significant at p = 0.000. The level 1 residual variance component of 0.585 indicates remaining within-student variation.

Table 6 displays the fixed effects for the final model. No substantive differences were observed between the ordinary standard errors and the robust standard errors, indicating no substantial violations of data assumptions. There are seven fixed effects significant at $p < .05$, controlling for other variables in the model. Estimates of effect sizes for the fixed effects in the model were obtained by calculating (partial) r [$\sqrt{(t^2/(t^2 + df)}$] with small effects approximately represented by $r > 0.1$; medium effects represented by $r > 0.24$; and large effects represented by $r > 0.37$ (Kirk, 1996).

Table 4. Diagnostic statistics for the successive HLM analyses

Statistics for covariance components model					
Deviance = 10902.858325					
Number of estimated parameters = 18					
			df	Chi-Square	P value
Model comparison test (null vs final model)			15	1899.765	0.000
Test of homogeneity of level-1 variance			884	334.659	>.500
Effect size estimates based upon variance components					
	Model A	**Model B**	**Model C**	**Model D**	**Model E**
	Null (Empty)	**Baseline (Random Intercept)**	**Baseline (Random Intercept and Slopes)**	**Final (Random Intercept)**	**Final (Random Intercept and Slopes)**
INTERCEPT1	1.242*	1.235*	0.888*	0.278*	0.067
TIME slope			0.018		0.046*
LEVEL-1, E	0.737	0.721	0.683	0.690	0.585
TOTAL	1.979	1.955		0.968	
Effect size A: 1-(sum D/sum A) = 0.511					
Effect size B: 1-(sum D/sum B) = 0.505					

* significant at $p = 0.000$

Table 5. HLM model fit and random effects

Final estimation of level-1 and level-2 variance components (random intercepts and random slopes)					
Random Effect	Standard Deviation	Variance Component	df	Chi-square	P-value
INTERCEPT1, RO	0.258	0.067	1071	816.427	>.500
TIME slope, R1	0.215	0.0467	1071	1269.668	0.000
Level-1, E	0.765	0.5857			

Note: The chi-square statistics reported above are based on only 1078 of 1306 units that had sufficient data for computation. Fixed effects and variance components are based on all data.

From Table 6, beginning with effects on the intercept, the coefficient for gender is not significant. The coefficient for school B is significantly different from the reference Group, school C, ($p < .05$) with a very small effect size.

Of most interest are the effects for the learning strategies groups, which show significant differences. With the intercept of the high learning strategy group operating as the reference, (5.78), the coefficients for the intercepts for the other three groups reflect the differences between the four groups' mean Learning Strategies scores (-1.11 Med_Hi; -2.10 Low_Med; -3.29 Med_Hi). Effect sizes for differences between the groups on their intercepts are large, ranging from 0.50 to 0.80.

Next, the slope for time represents change for the reference group (boys, learning strategies group - high, school C). This means that for each one year increase in time, the reference group's Learning Strategies score reduced by -.03, which

Table 6. HLM fixed effects (with robust standard errors)

	Co-efficient	Standard Error	Approx T-ratio	d.f.	P-value	Effect size
For INTERCEPT 1, P0						
INTERCEPT 2, B00	5.78	0.06	99.39	1299	0.00	0.94
GENDER, B01	0.05	0.03	1.37	1299	0.17	0.04
SCHOOL A, B02	0.08	0.04	1.83	1299	0.07	0.05
SCHOOL B, B03	0.10	0.04	2.37	1299	0.02	0.07
STRATEGIES GROUP LOW, B04	-3.29	0.07	-47.52	1299	0.00	0.80
STRATEGIES GROUP LO-MED, B05	-2.10	0.05	-39.52	1299	0.00	0.74
STRATEGIES GROUP MED-HI, B06	-1.11	0.05	-20.77	1299	0.00	0.50
For TIME slope, P1						
INTERCEPT2, B10	-0.03	0.04	-0.62	1299	0.53	0.02
GENDER, B11	0.08	0.02	3.75	1299	0.00	0.10
SCHOOL A, B12	0.05	0.03	1.73	1299	0.08	0.05
SCHOOL B, B13	0.11	0.03	3.30	1299	0.00	0.09
STRATEGIES GROUP LOW, B14	-0.02	0.04	-0.54	1299	0.59	0.02
STRATEGIES GROUP LO-MED, B15	0.05	0.04	1.28	1299	0.20	0.04
STRATEGIES GROUP MED-HI, B16	0.00	0.04	0.00	1299	1.00	0.00

was not significant, controlling for other variables in the model.

The change over time (slope) for girls was significantly more positive than for boys ($p < .001$), with a small effect size, controlling for other variables in the model. A recalculation of the model with girls as the reference group also found no significant overall effect over time, even though there was a difference between boys and girls.

The change over time (slope) for school B was significantly more positive than the change over time for the reference group, school C ($p < .01$), with a small effect size, controlling for other variables in the model. Recalculations of the model, whereby each school was alternated as the reference group, found no overall significant effect over time, even though there were small differences between the schools.

There were no apparent differences between learning strategies groups in their rate of change over time, controlling for other variables in the model.

To summarise, the major findings of interest for this paper are the large learning strategies group effects on the intercept, associated with the lack of significant change over time, for all four learning strategies groups, in mean scores over five years of secondary schooling. Small differences between the three schools and boys/girls were also apparent.

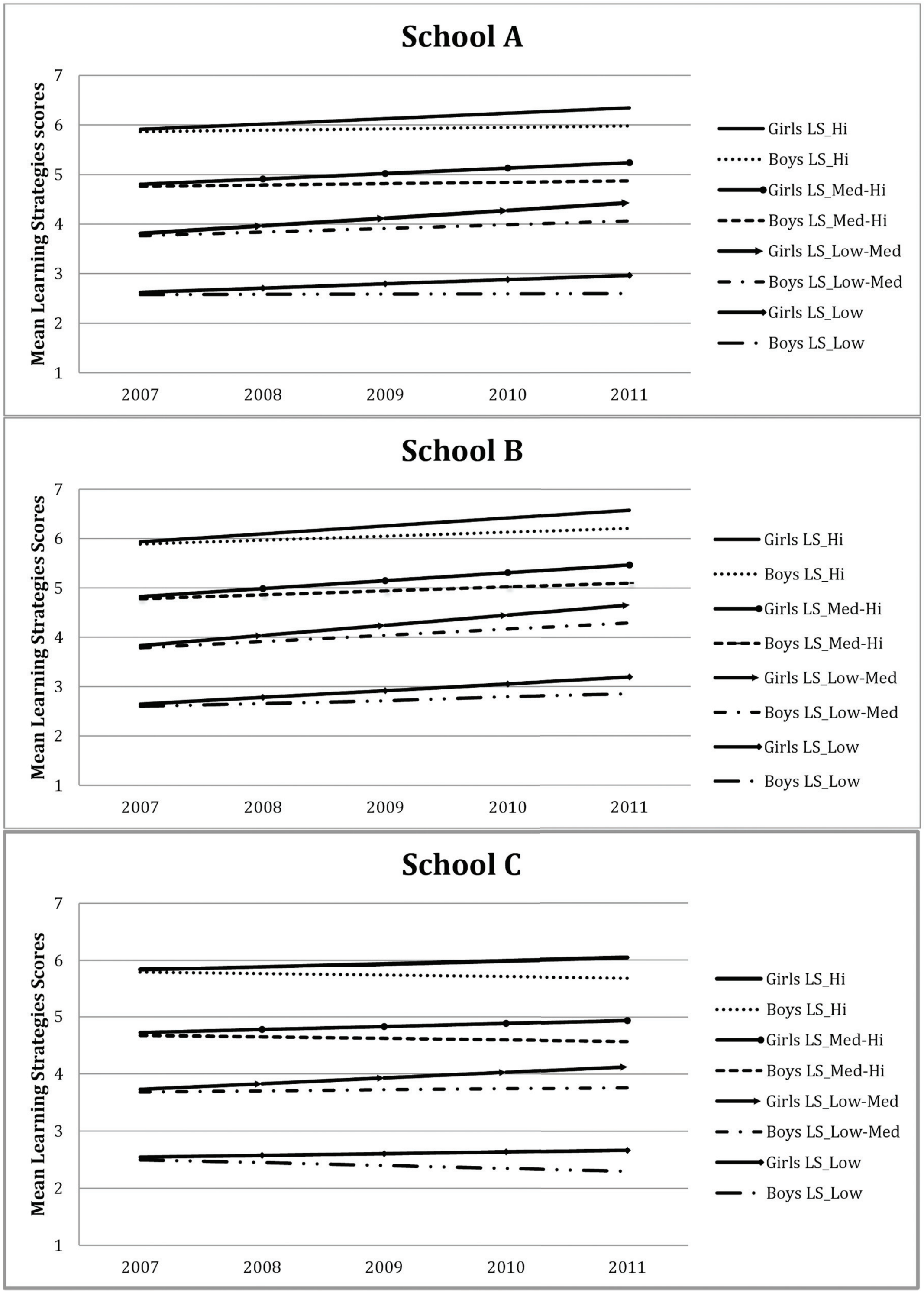
DISCUSSION AND CONCLUSION

To assist with conceptualising the above results, we used the coefficients in Table 6 to create Figure 3, which displays the estimated mean Learning Strategies scores for boys and girls, for each of the four learning strategies groups, in each school.

Of immediate concern is that students' reports of their learning strategy use do not increase much over five years, even though it might be anticipated that as school work increases in complexity, good quality learning strategies would be highly advantageous. Secondly, it is notable that the separation between the learning strategy groups, which was determined in the first year of data collection, remains over the five years (recall that this is even with the use of "corrected" scores to accommodate potential regression to the mean). In none of the three schools did a lower group move up into the trajectory of a higher group. In school A, the trajectories for girls rise slightly but for boys are virtually flat. In school B, trajectories for girls and boys rise slightly. In school C the trajectories for girls and boys show very little growth. Importantly, in all schools, the trajectories for the lowest two groups barely rise above the mid point of the Learning Strategies scale, indicating that students in these groups report that they use the strategies identified in our questionnaire relatively infrequently at the beginning, and at the end, of their schooling.

In summary, our findings did not support our hope that as students progressed through high school there would be evidence of more frequent use of useful learning strategies. Why might this be so? According to Dignath-van Ewik and van der Werf (2012, p.8) "the area of direct strategy instruction has somehow got lost in teachers' minds (or has never existed)". Similarly, Dunlosky (2013) noted that some teachers tend to over-emphasise the importance of the subject-matter content of their lessons and undervalue the advantages associated with detailed learning strategy knowledge. Such teachers are content to rely heavily on strategies such as highlighting and repetition which, while important, cannot substitute for strategies that support other key components of self-regulated learning, such as metacognitive knowledge. In a reciprocal fashion, some students lack knowledge about, or undervalue, good quality learning strategies (Hogan, 1999; Malmberg et al., 2013). Students need knowledge about strategies for self-regulated learning, because in a typical classroom group-learning situation they must direct much of their own learning: A single teacher has very limited time for one-on-one interaction

Figure 3. Estimated mean Learning Strategies scores



with students (Black, 2004; Galton & Pell, 2012). Galton and Pell found that the largest groups of engaged students they observed (43.8%) adopted what they termed a solitary worker approach, in which, "Although they sit in groups, for nearly 70% of the time they work on their own. Their contact with the teacher mainly involves being part of his/her audience when nobody in the class is in focus" (p.29). As Hattie (2009) noted, most students are, in a real sense, acting as their own teachers. The disappointing results for growth in students' cognitive and metacognitive strategy use reported in this chapter lends support to the need for explicit cognitive and metacognitive strategy instruction in the secondary school years.

ACKNOWLEDGMENT

The authors would like to thank Dr Mirella Wyra for her valuable assistance in data collection and data management, without which this study would not have been possible.

This research was supported by grants from the Australian Research Council and Flinders University.

REFERENCES

ACARA. (2011). *The national assessment program – Literacy and numeracy (NAPLAN).* Retrieved Aug 14, 2013, from http://www.nap.edu.au/naplan/naplan.html

Alexander, P. A., Jetton, T. L., & Kulikowich, J. M. (1995). Interrelationship of knowledge, interest and recall: Assessing a model of domain learning. *Journal of Educational Psychology*, *87*(4), 559–575. doi:10.1037/0022-0663.87.4.559

Askell-Williams, H., Lawson, M. J., & Skrzypiec, G. (2012). Scaffolding cognitive and metacognitive strategy instruction in regular class lessons. *Instructional Science*, *40*(2), 413–443. doi:10.1007/s11251-011-9182-5

Bartlett, M. S. (1954). Note on the multiplying factors for various chi square approximations. *Journal of the Royal Statistical Society, 16*(Series B), 296-298.

Beuhring, T., & Kee, D. W. (1987). Developmental relationships among metamemory, elaborative strategy use, and associative memory. *Journal of Experimental Child Psychology*, *44*(3), 377–400. doi:10.1016/0022-0965(87)90041-5

Black, L. (2004). Teacher-pupil talk in whole class discussions and processes of social positioning within the primary school classroom. *Language and Education*, *18*(5), 347–360. doi:10.1080/09500780408666888

Boekaerts, M., & Corno, L. (2005). Self-regulation in the classroom: A perspective on assessment and intervention. *Applied Psychology*, *54*(2), 199–231. doi:10.1111/j.1464-0597.2005.00205.x

Bransford, J. D., Brown, A. L., & Cocking, R. R. (2000). *How people learn: Brain, mind, experience, and school (Expanded edition)*. Washington, DC: National Academy Press.

Brown, A. L., Bransford, J. D., Ferrara, R. A., & Campione, J. C. (1983). Learning, remembering, and understanding. In P. H. Mussen (Ed.), Handbook of child psychology: Vol. 3. *Cognitive development* (pp. 77–166). New York: Wiley.

Bryk, A. S., & Raudenbush, S. W. (2002). *Hierarchical linear model: Applications and data analysis methods* (2nd ed.). Newbury Park, CA: Sage.

Chi, M. T. H. (1985). Interactive roles of knowledge and strategies in the development of organised sorting and recall. In J. W. Segal, S. F. Chipman, & R. Glaser (Eds.), *Thinking and learning skills* (Vol. 1, pp. 457–483). Hillsdale, NJ: Erlbaum.

Dignath-van Ewijk, C., & van der Werf, G. (2012). What teachers think about self-regulated learning: Investigating teacher beliefs and teacher behavior of enhancing students' self-regulation. *Education Research International*, *2012*, 1–10. doi:10.1155/2012/741713

Dunlosky, J. (2013). Strengthening the student toolbox: Study strategies to boost learning. *American Educator*, *37*, 12–21.

Efklides, A. (2011). Interactions of metacognition with motivation and affect in self-regulated learning: The MASRL model. *Educational Psychologist*, *46*(1), 6–25. doi:10.1080/00461520.2011.538645

Field, A. (2006). *Discovering statistics using SPSS* (3rd ed.). London: Sage.

Galton, M., & Pell, T. (2012). Do class size reductions make a difference to classroom practice? The case of Hong Kong primary schools. *International Journal of Educational Research*, *53*, 22–31. doi:10.1016/j.ijer.2011.12.004

Garson, D. G. (Ed.). (2013). *Hierarchical linear modelling*. Thousand Oaks, CA: Sage. doi:10.4135/9781483384450

Hadwin, A. F., & Winne, P. W. (2012). Promoting learning skills in undergraduate students. In J. R. Kirby & M. J. Lawson (Eds.), *Enhancing the quality of learning* (pp. 210–227). New York: Cambridge University Press; doi:10.1017/CBO9781139048224.013

Hattie, J. (2009). *Visible learning*. Oxon, UK: Routledge.

Hogan, K. (1999). Thinking aloud together: A test of an intervention to foster students' collaborative scientific reasoning. *Journal of Research in Science Teaching*, *36*(10), 1085–1109. doi:10.1002/(SICI)1098-2736(199912)36:10<1085::AID-TEA3>3.0.CO;2-D

Hübner, S., Nückles, M., & Renkl, A. (2010). Writing learning journals: Instructional support to overcome learning-strategy deficits. *Learning and Instruction*, *20*(1), 18–29. doi:10.1016/j.learninstruc.2008.12.001

Kaiser, H. (1970). A second generation Little Jiffy. *Psychometrika*, *35*(4), 401–415. doi:10.1007/BF02291817

Kaiser, H. (1974). An index of factorial simplicity. *Psychometrika*, *39*(1), 31–36. doi:10.1007/BF02291575

Kiewra, K. A. (2002). How classroom teachers can help students learn and teach them how to learn. *Theory into Practice*, *41*(2), 71–80. doi:10.1207/s15430421tip4102_3

Kirk, R. E. (1996). Practical significance: A concept whose time has come. *Educational and Psychological Measurement*, *56*(5), 746–759. doi:10.1177/0013164496056005002

Klauer, K. J. (1988). Teaching for learning-to-learn: A critical appraisal with some proposal. *Instructional Science*, *17*(4), 351–367. doi:10.1007/BF00056221

Malmberg, J., Järvenoja, H., & Järvelä, S. (2013). Patterns in elementary school students′ strategic actions in varying learning situations. *Instructional Science*, *41*(5), 1–22. doi:10.1007/s11251-012-9262-1

Mayer, R. (1998). Cognitive, metacognitive, and motivational aspects of problem solving. *Instructional Science*, *26*(1/2), 49–63. doi:10.1023/A:1003088013286

Midgley, C., Maehr, M. L., Hruda, L. Z., Anderman, E., Anderman, L., Freeman, K. E., … Urdan, T. (2000). *Manual for the patterns of adaptive learning scales.* Retrieved March 31, 2013, from http://www.umich.edu/~pals/manuals.html

Nelson, T. O. (1996). Consciousness and metacognition. *The American Psychologist*, *51*(2), 102–116. doi:10.1037/0003-066X.51.2.102

Nielsen, T., Karpatschof, B., & Kreiner, S. (2007). Regression to the mean effect: When to be concerned and how to correct for it. *Nordic Psychology*, *59*(3), 231–250. doi:10.1027/1901-2276.59.3.231

Novak, J. D. (1990). Concept maps and Vee diagrams: Two metacognitive tools to facilitate meaningful learning. *Instructional Science*, *19*(1), 29–52. doi:10.1007/BF00377984

OECD. (n.d.). *OECD programme for international student assessment.* Retrieved August 14, 2013, from http://www.oecd.org/pisa/

Palardy, G. J. (2013). Random coefficients modelling with HLM. In G. D. Garson (Ed.), *Hierarchical linear modelling: Guide and applications* (pp. 183–218). Thousand Oaks, CA: Sage. doi:10.4135/9781483384450.n8

Pintrich, P. R. (2004). A conceptual framework for assessing motivation and self-regulated learning in college students. *Educational Psychology Review*, *16*(4), 385–407. doi:10.1007/s10648-004-0006-x

Pintrich, P. R., & DeGroot, E. V. (1990). Motivational and self-regulated learning components of classroom academic performance. *Journal of Educational Psychology*, *82*(1), 33–40. doi:10.1037/0022-0663.82.1.33

Roebers, C., Cimeli, P., Röthlisberger, M., & Neuenschwander, R. (2012). Executive functioning, metacognition, and self-perceived competence in elementary school children: An explorative study on their interrelations and their role for school achievement. *Metacognition and Learning*, *7*(3), 151–173. doi:10.1007/s11409-012-9089-9

Schneider, W. (2010). Metacognition and memory development in childhood and adolescence. In H. S. Waters & W. Schneider (Eds.), *Metacognition, strategy use, and instruction* (pp. 54–81). New York: Guilford Press.

Schraw, G., Crippen, K. J., & Hartley, K. (2006). Promoting self-regulation in science education: Metacognition as part of a broader perspective on learning. *Research in Science Education*, *36*(1-2), 111–139. doi:10.1007/s11165-005-3917-8

Schraw, G., & Dennison, R. S. (1994). Assessing metacognitive awareness. *Contemporary Educational Psychology*, *19*(4), 460–475. doi:10.1006/ceps.1994.1033

Schunk, D. H., & Zimmerman, B. J. (Eds.). (1989). *Self regulated learning and academic achievement: Theory, research and practice*. New York: Springer Verlag.

Schunk, D. H., & Zimmerman, B. J. (2013). Self-regulation and learning. In W. M. Reynolds, G. E. Miller, & I. B. Weiner (Eds.), Handbook of psychology: Vol. 7. *Educational psychology* (2nd ed., pp. 45–68). Hoboken, NJ: John Wiley & Sons.

Schwonke, R., Ertelt, A., Otieno, C., Renkl, A., Aleven, V., & Salden, R. J. C. M. (2013). Metacognitive support promotes an effective use of instructional resources in intelligent tutoring. *Learning and Instruction*, *23*, 136–150. doi:10.1016/j.learninstruc.2012.08.003

Sitzman, T., & Ely, K. (2011). A meta-analysis of self-regulated learning in work-related training and educational attainment: What we know and where we need to go. *Psychological Bulletin*, *137*(3), 421–442. doi:10.1037/a0022777 PMID:21401218

Snijders, T. A. B., & Bosker, R. J. (2012). *Multilevel analysis* (2nd ed.). London: Sage.

van der Stel, M., & Veenman, M. V. J. (2010). Development of metacognitive skillfulness: A longitudinal study. *Learning and Individual Differences*, *20*(3), 220–224. doi:10.1016/j.lindif.2009.11.005

Veenman, M. V. J., & Veenman, M. V. J. (2011). Alternative assessment of strategy use with self-report instruments: A discussion. *Metacognition and Learning*, *6*(2), 205–211. doi:10.1007/s11409-011-9080-x

Weinstein, C. E., & Mayer, R. E. (1986). The teaching of learning strategies. In C. M. Wittrock (Ed.), *Handbook of research in teaching* (pp. 315–327). New York: Macmillan.

Winne, P. H. (2005). A perspective on state-of-the-art research on self-regulated learning. *Instructional Science*, *33*(5-6), 559–565. doi:10.1007/s11251-005-1280-9

Zimmerman, B. J. (2002). Becoming a self-regulated learner. *Theory into Practice*, *41*(2), 65–70. doi:10.1207/s15430421tip4102_2

Zimmerman, B. J., & Martinez-Pons, M. (1990). Student differences in self-regulated learning: Relating grade, sex, and giftedness to self-efficacy and strategy use. *Journal of Educational Psychology*, *82*(1), 51–59. doi:10.1037/0022-0663.82.1.51

ADDITIONAL READING

Anderson, J. R., & Fincham, J. M. (2014). Extending problem-solving procedures through reflection. *Cognitive Psychology*, *74*, 1–34. doi:10.1016/j.cogpsych.2014.06.002 PMID:25063939

Ariel, R. (2013). Learning what to learn: The effects of task experience on strategy shifts in the allocation of study time. *Journal of Experimental Psychology. Learning, Memory, and Cognition*, *39*(6), 1697–1711. doi:10.1037/a0033091 PMID:23751010

Askell-Williams, H., & Lawson, M. J. (2006). Multidimensional profiling of medical students' knowledge about learning. *Medical Education, 40*, 138-145. doi: org/10.1111/j.1365-2929.2005.02369.x

Bryce, D., & Whitebread, D. (2012). The development of metacognitive skills: Evidence from observational analysis of young children's behavior during problem-solving. *Metacognition and Learning*, *7*(3), 197–217. doi:10.1007/s11409-012-9091-2

Kistner, S., Rakoczy, K., Otto, B., Dignath-van Ewijk, C., Buttner, G., & Klieme, E. (2010). Promotion of self-regulated learning in classrooms: Investigating frequency, quality, and consequences for student performance. *Metacognition and Learning*, *5*(2), 157–171. doi:10.1007/s11409-010-9055-3

Lawson, M. J., & Askell-Williams, H. (2011). Framing the features of good quality knowledge for teachers and students. In M. J. Lawson & J. R. Kirby (Eds.), *The quality of learning: dispositions, instruction, and mental structures*. New York: Cambridge University Press.

Lawson, M. J., Barnes, A., White, B., & Askell-Williams, H. (2014). Concerns about the quality and quantity of students' knowledge about learning. In T. C. Papadopoulos, R. K. Parrila, & J. R. Kirby (Eds.), *Cognition, intelligence, and achievement: A tribute to J. P. Das*. London: Academic Press.

Leopold, C., Sumfleth, E., & Leutner, D. (2013). Learning with summaries: Effects of representation mode and type of learning activity on comprehension and transfer. *Learning and Instruction*, *27*, 40–49. doi:10.1016/j.learninstruc.2013.02.003

Mega, C., Ronconi, L., & De Beni, R. (2013). What makes a good student? How emotions, self-regulated learning, and motivation contribute to academic achievement. *Journal of Educational Psychology*, *106*(1), 121–131. doi:10.1037/a0033546

Miller, T. M., & Geraci, L. (2011). Training metacognition in the classroom: The influence of incentives and feedback on exam predictions. *Metacognition and Learning*, *6*(3), 303–314. doi:10.1007/s11409-011-9083-7

Molenaar, I., van Boxtel, C. A. M., & Sleegers, P. J. C. (2010). The effects of scaffolding metacognitive activities in small groups. *Computers in Human Behavior*, *26*(6), 1727–1738. doi:10.1016/j.chb.2010.06.022

Pressley, M., & Harris, K. R. (2006). *Cognitive strategies instruction: From basic research to classroom instruction. Handbook of educational psychology* (pp. 265–286). Mahwah, NJ: Erlbaum.

Rachal, K. C., Daigle, S., & Rachal, W. S. (2007). Learning problems reported by college students: Are they using learning strategies? *Journal of Instructional Psychology*, *34*, 191–199.

Tran, T. A. T., & Lawson, M. (2007). Students' pedagogical knowledge about teachers' use of questions. *International Education Journal*, *8*, 418–432.

Virtanen, P., & Nevgi, A. (2010). Disciplinary and gender differences among higher education students in self-regulated learning strategies. *Educational Psychology*, *30*(3), 323–347. doi:10.1080/01443411003606391

Winne, P. H. (2010). Improving measurements of self-regulated learning. *Educational Psychologist*, *45*(4), 267–276. doi:10.1080/00461520.2010.517150

Zimmerman, B. J., & Schunk, D. H. (2011). Handbook of self-regulation of learning and performance (pp. xiv, 484). New York, NY: Routledge.

KEY TERMS AND DEFINITIONS

Cognitive Strategies: Strategies for learning subject-matter, such as generating questions, taking notes, making mental images, and drawing concept maps (Kiewra, 2002; Novak, 1990).

Effect Size: A measure that describes the size of the difference between two groups.

Hierarchical Linear Modelling (HLM): Hierarchical linear models and multilevel models are variant terms for what are broadly called linear mixed models (LMM). These models handle data where observations are not independent, correctly modeling correlated error… [adjusting] observation-level predictions based on the clustering of measures at some higher level or by some grouping variable (Garson, 2013, pp. 3-4).

Metacognitive Knowledge and Control: Declarative, procedural, and conditional knowledge, and regulation (including planning, monitoring, evaluation), that directs the use of cognitive strategies (Schraw et al., 2006).

Self-Regulated Learning: The modulation of affective, cognitive, and behavioral processes throughout a learning experience to reach a desired level of achievement (Sitzman & Ely, 2011, p.421).

ENDNOTES

1 The Index of Educational Disadvantage was developed using a combination of Education Department and Australian Bureau of Statistics data. It groups all schools into one of seven ranks of educational disadvantage based on four measures: parental income; parental education and occupation; Aboriginality; and student mobility.

[2] With only three schools, it was not possible to undertake 3-level HLM, as there would have been too few units at level three of the model (Garson, 2013). We therefore used two-level HLM, and added SCHOOL as a dummy variable at level 2.

[3] The percentage of variance accounted for at level 2 equates to the Intraclass Correlation, i.e., (1.24/[1.24 + .73]) = 0.63.

[4] TIME was also tested as a quadratic variable, but the effects were trivial.