Theories of Intelligence, Metacognition, and Teaching Strategies in Student Achievement

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Abstract

Undergraduate science, technology, engineering, and mathematics (STEM) fields in the United States experience high attrition rates, with many students either switching to non-STEM fields or leaving college entirely. Education researchers and reformers have proposed that STEM education can be improved by developing a better understanding of the motivational processes underlying learning. Past studies have suggested that student theories of intelligence inform the engagement of adaptive learning strategies such as metacognition and consequently course achievement, without necessarily taking teaching strategies into consideration. This study examines the impact of an active learning pedagogical approach, broadly defined as any non-lecture teaching format, on metacognition. Data from students in two undergraduate science lecture courses—one taught by an instructor using an active learning pedagogy, the other taught by an instructor using a traditional lecture style—was studied. The first set of analyses provided support for a learning process model in which metacognition allows for the engagement of other adaptive learning strategies, leading to higher achievement. The second set of analyses indicated that metacognition is associated with a significant increase in course grade independent of theory of intelligence. The third set of analyses indicated that an active learning instructional style is associated with a significant increase in student metacognition, also independent of theory of intelligence. These results suggest that instructional pedagogies should decenter theories of intelligence and prioritize the teaching of metacognitive skills.

Introduction

Undergraduate education in science, technology, engineering, and mathematics (STEM) continues to be a national priority. American students lag behind students from comparable nations in high school scientific and mathematical literacy, as well as in science and engineering degree achievement. In 2007, the federal effort to bolster STEM education was estimated at three billion dollars (Kuenzi, 2008), and efforts have continued since then, including, more recently, President Barack Obama's 2013 Federal STEM Education 5-Year Strategic Plan (Holdren et al., 2013).

At the undergraduate level, STEM education is plagued by high attrition rates. Of students who started STEM bachelor's degrees between 2003 and 2009, 48 percent had either changed majors to a non-STEM field or left college without earning a degree by spring of 2009. Furthermore, women, underrepresented minorities, first-generation students, and students from low-income backgrounds are more likely to leave STEM fields than other students (Chen, 2013).

STEM education researchers and reformers propose that revised approaches to teaching, informed by an understanding of the cognitive and motivational processes underlying learning, can help to improve STEM education by increasing student engagement and achievement and decreasing attrition (Freeman et al., 2014). Empirical research into the factors underlying student learning is necessary to improve teaching pedagogies and, subsequently, student achievement and persistence in STEM. Exploration of this area is necessary not only to improve the standing of the United States internationally, but also to decrease inequities at the domestic level.

Learning Orientations and Implicit Theories of Intelligence

Previous research indicates that students' motivational patterns, based at least in part on beliefs about their own intelligence, have a significant impact on academic achievement. Dweck and Leggett (1988) distinguish between two types of student goal orientations. Students with a *performance* goal orientation are motivated by a desire for positive judgments of their competence, whereas students with a *learning* goal orientation are motivated by a desire to increase their competence. Dweck and Leggett propose that a student's implicit theory of intelligence—the way the student conceptualizes ability—is a significant causal factor determining the student's goal orientation. Students with an *entity* theory of intelligence believe that intelligence is fixed and uncontrollable, and will adopt a performance goal orientation, whereas students with an *incremental* theory of intelligence believe that intelligence is malleable and controllable, and will adopt a learning goal orientation. The causal relationship between implicit theory of intelligence and goal orientation is supported by both correlational (Dweck & Bempechat, 1983) and experimental research (Dweck, Tenney, and Dinces, 1982).

Further research indicates that students with learning goal orientations use more adaptive strategies than students with performance goal orientations. In a study of junior high and high school students, those who held learning goals were more likely to use effective learning strategies, prefer challenging tasks, and report greater enjoyment of the class, controlling for perceived ability (Ames & Archer, 1988). In a study of college undergraduates, Schraw et al. (1995) found that students with a high learning orientation reported greater usage of learning strategies involving integration, organization, memorization, and metacognitive awareness and also attained higher course achievement, controlling for prior achievement. These findings suggest the existence of a learning process pathway in which an incremental theory of intelligence gives way to a learning goal orientation, which spurs greater usage of adaptive learning strategies and subsequently higher achievement (Figure 1).

Figure 1. Learning process model proposed by the existing theoretical literature.

Adaptive Learning Strategies and Metacognition

The Motivated Strategies for Learning Questionnaire (Pintrich et al., 1991) provides one of the most popular taxonomies of adaptive learning strategies. The MSLQ divides learning strategies into three broad categories: cognitive, metacognitive, and resource management. Cognitive strategies include strategies based on rehearsal (i.e. "I memorize key words"), elaboration (i.e. "I try to relate ideas in this subject to those in other courses"), organization (i.e. "I make simple charts to organize course material"), and critical thinking (i.e. "Whenever I read an assertion in this class, I think about possible alternatives"). Metacognitive strategies involve students' awareness, knowledge, and control of cognition (i.e. "When studying for this course I try to determine which concepts I don't understand well"). Resource management strategies include strategies based on time and study environment management (i.e. "I have a regular place set aside for studying"), effort regulation (i.e. “I work hard to do well in this class even if I don’t like what we are doing”), peer learning (i.e. “I try to work with other students from this class”), and help seeking (i.e. “I ask the instructor to clarify concepts I don’t understand well”). The MSLQ also includes four subscales assessing student motivational factors, including theory of intelligence and learning orientation.

Corno (1986) proposes that metacognitive strategies may play a special role in learning, since they are necessary for maintaining system efficiency. Evidence supports the link between metacognition and achievement. In a study of high school English students, Landine & Stewart (1998) found a significant positive relationship between metacognitive strategy use and academic success. Vrugt & Oort (2007), in a study of undergraduate psychology students, found that the use of metacognitive strategies was related to higher exam scores. Ford et al. (1998) found that participants with higher metacognitive ability developed greater knowledge of and strategies for a computer task, and subsequently displayed stronger performance, suggesting that metacognition may be crucial in making the employment of other types of adaptive learning strategies possible. The research further suggests a positive relationship between a learning goal orientation and metacognition (Ford et al., 1998; Landine & Stewart, 1998; Vrugt & Oort, 2007). The authors propose that individuals who approach a task with the goal of mastery will more effectively understand and regulate their own learning, rather than opting for rote learning strategies. Thus, in existing models, metacognition is conceptualized as an effect of a learning goal orientation. Further, greater metacognition is related to higher achievement, possibly because it enables the usage of other adaptive learning strategies.

Teaching Strategies

The MSLQ is based on a social-cognitive view of motivation and learning (Duncan & McKeachie, 2005) in which the student's behavior is produced by the interactions between a variety of environmental and personal variables (Schunk & Zimmerman, 1997). In this model, a student may display different motivational and behavioral patterns depending on the specific task or situation; for example, the student may display less intrinsic motivation for a course in a subject area of less personal interest, or be less likely to initiate group study if doing so seems contrary to a specific classroom's culture. A meta-analysis of studies using the MSLQ as a measure found significant variation in motivations and learning strategies for the same individual across different courses. Furthermore, a student's score on the MSLQ for a particular course was consistently more strongly related to performance in that course than to overall performance (Crede & Phillips, 2011). The social-cognitive model, supported by this data, undercuts the centrality of personality characteristics like theory of intelligence as factors determining student motivation and highlights the importance of situation-specific factors.

Much of the existing literature studies motivation and behavior at the student level, without taking into consideration these situation-specific factors (Ames & Archer, 1988; Dweck & Bempechat, 1983; Dweck, Tenney, and Dinces, 1982; Ford et al., 1998; Landine & Stewart, 1998; Schraw et al., 1995; Vrugt & Oort, 2007). In particular, little work exists relating teaching strategies to student motivation and learning strategy usage. A model of student learning, however, is incomplete without the inclusion of teaching strategies.

Recent research in undergraduate science education has suggested the efficacy of active learning approaches over lecture formats in improving student outcomes, including academic achievement (Freeman et al., 2014) and college persistence rates (Braxton et al., 2008). Active learning is broadly defined as any non-lecture teaching format, and includes approaches ranging from group problem-solving to in-class worksheets to the use of personal response systems (Freeman et al., 2014). In active learning approaches, students become active participants in the creation of knowledge rather than passive recipients of knowledge. A taxonomy of active learning pedagogies, developed by Couch et al. (2015), can be found in Appendix A.

Efforts to increase the usage of active learning pedagogies in college science classrooms include the Summer Institutes on Scientific Teaching (SI), sponsored by the Howard Hughes Medical Institute and the National Science Foundation. Since 2004, the SI has trained over 2,000 STEM faculty members in evidence-based teaching through regionally-based multiple-day workshops[1]. Faculty members receive practice developing instructional materials with active learning approaches, as well as the theory and research behind these approaches. SI facilitators lead the workshops with active learning principles in mind, and so SI participants partake in significant amounts of group work, interactive presentations, reflective exercises, and more. SI participants report implementing strategies learned at the workshops in their classrooms at high rates, as well as improved performance by their students (Pfund et al., 2009). Cavanagh et al. (2016) studied student perceptions of active learning in classrooms taught by SI-trained instructors, and found that greater student buy-in to active learning—consisting of exposure, persuasion, identification, and commitment to active learning pedagogies—resulted in increased course engagement and higher final course grades.

[1] www.summerinstitutes.org

Much of the research on the SI and active learning in general is evaluative in nature. This research, discussed above, seeks to determine the efficacy of pedagogical approaches in terms of increasing student grades and persistence in STEM fields, often for the purpose of justifying continued support for programs such as the SI. However, situating this evaluative research within the broader theoretical context of social-cognitive learning can allow us to develop a deeper, more generalizable understanding of learning. By probing the psychological mechanisms underlying the efficacy of active learning, we can fine-tune active learning pedagogy and improve learning for students not just in science fields but in all fields. While most contemporary research on active learning focuses on STEM courses due to the interest on increasing performance in these areas, its core principle of engaging students as active constructors of knowledge is relevant across disciplines (Bonwell & Eison, 1991). Although this study focuses on students enrolled in STEM courses, by looking beyond purely evaluative research questions towards more theoretical ones, we may be able to explore how learning works across disciplines.

Summary

The existing literature proposes the existence of a learning process model in which an incremental theory of intelligence causes a learning goal orientation, which enables the employment of adaptive learning strategies and subsequently greater academic achievement (Figure 1). Evidence exists that, among these adaptive learning strategies, metacognition may play a special role by enabling the employment of other strategies.

This model places at its foundation student characteristics: theory of intelligence and learning orientation. However, this conception of learning is at odds with the social-cognitive model, which states that situation-specific factors exert a significant influence on student motivational and behavioral patterns. A notable situation-specific factor influencing student learning is instructional pedagogy. The employment of active learning pedagogies by instructors has been shown to have a measurable impact on students. Further, active learning may specifically increase student metacognition by exposing students to unique learning strategies and encouraging students to reflect on the personal effectiveness of these strategies (Vos & De Graaff, 2004). This increase in metacognition may then, as some prior research has proposed, spur the adoption of other non-metacognitive adaptive learning strategies, leading to higher achievement. It is therefore possible that the influence of student-level characteristics such as theory of intelligence on metacognition and subsequent achievement may be mitigated by the presence of a strong, active-learning pedagogy introduced by the instructor. Student buy-in to active learning may further bolster this effect.

Figure 2. Learning process model proposed in this paper, taking into account teaching strategies.

The purpose of this present study is to examine the relationships between theory of intelligence, metacognition, and achievement in an active learning environment. Specifically, this study aims to address the following questions:

1. Is there support for a learning pathway in which metacognitive self-regulation makes possible the employment of other adaptive learning strategies, allowing for greater achievement?
2. Can metacognition predict achievement independent of theory of intelligence?
3. Can the employment of active learning pedagogies by an instructor affect student engagement of metacognitive self-regulation, independent of theory of intelligence?
4. Can student buy-in to active learning pedagogies better predict engagement of metacognition than mere exposure to these pedagogies?

Methods

Context

The data analyzed in this study was collected in the fall of 2016 from students enrolled in two large science lecture courses at the University of Connecticut. One of the lectures, Human Anatomy & Physiology, was taught by an instructor who had attended a Summer Institute and was trained in Active Learning (AL) pedagogy. The other lecture, Animal Physiology, was taught by an instructor who had not attended a Summer Institute. Students were not randomly assigned to classrooms; therefore, the design of the current study is quasi-experimental.

Participants

All students enrolled in the courses were eligible for participation. Student participants included 422 students (81% of total enrollment; 66% female). Students from underrepresented minority (URM) groups in STEM, consisting of African American, Hispanic or Latino/Latina, American Indian, and Alaska Native students (Estrada et al., 2016), made up 22% of the participants. The majority of participants (95%) were enrolled in the course either for major or general education credit. The majority of participants were sophomores (45%), although juniors (28%) and seniors (22%) were also represented, as well as a small number of freshmen (3%).

Procedure

Students were offered a minimal amount of extra credit to complete a Qualtrics survey towards the end of the semester. Students did not face any penalty if they chose not to complete the survey.

Measures

Exposure and Buy-In to Pedagogies

Participants reported their exposure to 27 active learning pedagogies selected from the scientific teaching taxonomy developed by Couch et al. (2015), selecting one of three levels: "I did this," "I did not do this," or "I did this but I did not understand this." Pedagogies represented a broad variety of active learning strategies, such as "I provided feedback to my instructor on his or her teaching methods", "I answered questions in class using a clicker or other polling method", and "I identified appropriate strategies for solving different types of problems" (Appendix A). An exposure sum score was computed for each student by totaling the number of pedagogies out of 27 for which the participant responded "I did this."

Participants who reported being exposed to and understanding a given pedagogy were subsequently prompted to report their buy-in to each of these pedagogies by responding “Yes” or “No” to each of the following statements concerning the pedagogy: “I was convinced that this was good” (Persuasion), “I did this because I believed it would contribute to my learning in a positive way” (Identification), and “I am committed to embracing this as a way of learning” (Commitment). Sum scores were calculated for each of these three subscales (Persuasion, Identification, and Commitment) by totaling the number of “Yes” responses within each subscale, again with a maximum possible value of 27. An overall buy-in sum score was then calculated by adding together the individual sum scores for persuasion, identification, and commitment. These subscales are aligned with the adoption process model proposed by Cavanagh et al. (2016), according to which student buy-in—comprised of persuasion, identification, and commitment, the steps following mere exposure to a pedagogy by the instructor—is a key factor leading to self-regulated learning and achievement.

Theory of intelligence score

Participants’ implicit theories of intelligence were measured using a three-item survey developed by Dweck (Blackwell et al., 2007). Participants used a six-point Likert scale to indicate their agreement with three statements: “You have a certain amount of intelligence, and you really can't do much to change it”, “Your intelligence is something about you that you can't change very much”, and “You can learn new things, but you can't really change your basic intelligence.” Responses were reverse-coded so a lower score indicated greater endorsement of an entity theory of intelligence, and a mean score (hereby referred to as "theory of intelligence mean") was computed for each participant.

Metacognitive Self-regulation

Participants' metacognitive self-regulation was measured using a subset of the Metacognitive Self-Regulation subscale of the Motivated Strategies for Learning Questionnaire (Pintrich et al., 1991). The MSLQ shows robust scale reliability, good factor structure, and reasonable predictive validity (Pintrich et al., 1993). Students rated their agreement with seven items using a seven-point Likert scale. Items included statements such as "When reading for this course, I make up questions to help focus my reading" and "When I study for this class, I set goals for myself in order to direct my activities in each study period" (full list of items in Appendix B). A mean score (hereby referred to as "metacognitive self-regulation mean") was computed for each participant.

Non-Metacognitive Adaptive Learning Strategies

Participants' usage of non-metacognitive adaptive learning strategies was measured using a subset of the rehearsal, elaboration, organization, critical thinking, time and study environment, effort regulation, peer learning, and help seeking subscales of the Motivated Strategies for Learning Questionnaire (Pintrich et al., 1991). Students rated their agreement with 19 items using a seven-point Likert scale. Items included statements such as "When I study for this course, I write brief summaries of the main ideas from the readings and my class notes" and "I have a regular place set aside for studying" (full list of items in Appendix C). A mean score (hereby referred to as “adaptive learning strategies mean”) was computed for each participant.

Final course grade

Participants reported their expected anticipated final grade in the course as a letter grade ranging from A+ to F. Grades were numerically recoded in descending order, with A+ being recoded as 11 and F being recoded as 1.

Analyses

All analyses were executed using IBM SPSS 24.0 software. Hierarchical multiple regression analyses were used to study the relative strength of various predictors on anticipated final grade and metacognitive self-regulation, with predictors grouped into sequential blocks based on theoretical grounds.

Results

Is there support for a learning pathway in which metacognitive self-regulation makes possible the employment of other adaptive learning strategies, allowing for greater achievement?

One-way ANOVAs were used to determine demographic factors that had significant effects on anticipated final grade, in order to control for these factors in subsequent hierarchical multiple regression analyses. Significant effects were found for gender ($F(3, 417) = 4.89$, $p = .002$), URM status ($F(1, 416) = 8.03$, $p = .005$), and cumulative GPA ($F(4, 412) = 51.13$, $p = .000$).

A series of hierarchical multiple regressions was used to determine whether adaptive learning strategies mean mediated the relationship between metacognitive self-regulation mean and anticipated final grade, controlling for demographic factors. Preliminary analyses ensured that the assumptions of normality, linearity, and homoscedasticity were not violated. The correlations between the continuous predictor variables (cumulative GPA, metacognitive self-regulation mean, and adaptive learning strategies mean) were examined, as were the correlations between the predictors and the dependent variable (anticipated final grade). These correlations are presented in Table 1. Correlations between predictors were generally weak, indicating that multicollinearity was unlikely. A high correlation ($r = .79$, $p < .001$) was found between metacognitive self-regulation mean and adaptive learning strategies mean, providing support for a mediational relationship.

Table 1. Descriptive statistics, reliability, and correlations for all continuous variables (N = 416)

Variables	FG	CG	TOI	M	A
Anticipated final grade (FG)	1				
Cum GPA (CG)	.58***	1			
Theory of intelligence mean (TOI)	.16***	.12**	1		
Metacognitive self-regulation mean (M)	.22***	.19***	.17***	1	
Adaptive learning strategies mean (A)	.23***	.18***	.19***	.79***	1
Means	7.10	3.02	4.25	4.95	4.90
Standard Deviations	2.15	.90	1,28	1.04	.80
Range	1.00-11.00	1.00-5.00	1.00-6.00	1.00-7.00	1.95-6.89
Possible range	1.00-11.00	1.00-5.00	1.00-6.00	1.00-7.00	1.00-7.00
Cronbach's Alpha	.56	.50	.60	.51	.52

Note. Statistical significance: *$p < .05$; **$p < .01$; ***$p < .001$

First, metacognitive self-regulation mean was established as a significant predictor of anticipated final grade independent of demographic factors, $\beta = .11$, $t(418) = 4.10$, $p < .01$. Second, metacognitive self-regulation mean was established as a significant predictor of adaptive learning strategies mean independent of demographic factors, $\beta = .79$, $t(420) = 26.12$, $p < .001$. Third, adaptive learning strategies mean was established as a significant predictor of anticipated final grade independent of demographic factors, $\beta = .15$, $t(419) = 3.62$, $p < .001$. Complete statistics for these regressions are included in Appendix D.

Finally, a multiple regression was conducted with both metacognitive self-regulation mean and adaptive learning strategies mean predicting anticipated final grade (Table 2). In this model, adaptive learning strategies mean is a significant predictor of anticipated final grade, $\beta = .16$, $t(418) = 2.39$, $p < .05$. However, metacognitive self-regulation mean is not a significant predictor of anticipated final grade, β = -.01, t(418) = -.22, p > .05. These results, in combination with the results from the previous regressions, indicate that adaptive learning strategies mean fully mediates the relationship between metacognitive self-regulation and anticipated final grade.

Table 2. Hierarchical Regression Model of anticipated final grade based on metacognitive self-regulation and adaptive learning strategies (N = 418)

	R	R^2	R^2 *Change*	*B*	*SE*	*β*	*t*
Step 1	.59	.34***					
URM Status				.03	.10	.01	.26
Gender				-.25	.08	-.13**	-3.22
Cum GPA				.57	.04	.57***	13.89
Step 2	.61	.37**	.02**				
URM Status				.00	.10	.00	-.02
Gender				-.27	.08	-.14***	-3.51
Cum GPA				.54	.04	.54***	13.08
Metacognitive self-regulation mean				-.01	.07	-.01	-.22
Adaptive learning strategies mean				.16	.07	.16*	2.39

Note. Statistical significance: *p < .05; **p < .01; ***p < .001

Can metacognitive self-regulation predict achievement independent of theory of intelligence?

A two-stage hierarchical multiple regression was conducted with anticipated final grade as the dependent variable. Preliminary analyses ensured that the assumptions of normality, linearity, and homoscedasticity were not violated. The correlations between the continuous predictor variables (cumulative GPA, theory of intelligence mean, and metacognitive self-regulation mean) were examined, as were the correlations between the predictors and the dependent variable (anticipated final grade). These correlations are presented in Table 1. Correlations between predictors were weak, indicating that multicollinearity was unlikely.

Gender, URM status, and cumulative GPA were entered at stage one of the regression to control for demographic factors affecting anticipated final grade. Theory of intelligence mean and metacognitive self-regulation mean were entered at stage two of the regression (Table 3). Introducing these predictors explained an additional 2% of variation in anticipated final grade, $p < .01$. In the final adjusted model, metacognitive self-regulation mean had a greater effect ($\beta = .10$, $p < .05$) than theory of intelligence mean ($\beta = .08$, $p < .05$).

Table 3. Hierarchical Regression Model of anticipated final grade (N = 418)

	R	R^2	R^2 *Change*	*B*	*SE*	*β*	*t*
Step 1	.59	.35***					
URM status				.03	.10	.01	.26
Gender				-.25	.08	-.13**	-3.22
Cum GPA				.57	.04	.57***	13.89
Step 2	.60	.37**	.02**				
URM status				.00	.10	.00	-.06
Gender				-.25	.08	-.13**	-3.27
Cum GPA				.54	.04	.54***	12.93
Theory of intelligence mean				.08	.04	.08*	2.06
Metacognitive self-regulation mean				.10	.04	.10*	2.38

Note. Statistical significance: *p < .05; **p < .01; ***p < .001

Can the employment of AL pedagogies by an instructor affect student engagement of metacognitive self-regulation, independent of theory of intelligence?

An independent-samples t-test was conducted to compare four sum scores (exposure, persuasion, identification, and commitment) between the non-AL and AL courses. A Bonferroni adjustment for multiple t-tests was made (Bonferonni-adjusted significance level = .0125). There was a significant difference in scores for non-AL exposure (M = 12.74, SD = 4.64) and AL exposure (M = 20.93, SD = 5.00), p =.000, non-AL persuasion (M = 9.02, SD = 5.16) and AL persuasion (M = 14.14, SD = 7.78), p =.000, non-AL identification (M = 7.56, SD = 4.67) and AL identification (M = 11.69, SD = 7.28), p =.000, and non-AL commitment (M = 7.05, SD = 5.09) and AL commitment (M = 8.91, SD = 7.54), p

=.010. These significant differences were used as a basis for treating the two courses as two separate conditions.

One-way ANOVAs were used to determine demographic factors that had significant effects on metacognitive self-regulation, in order to control for these factors in the subsequent hierarchical multiple regression analysis. Significant effects were found for cumulative GPA ($F(4, 414) = 8.59$, $p = .000$) and class status ($F(4, 416) = 3.00$, $p = .019$).

Pearson's chi-squared tests of independence were performed to examine the relation between condition and various demographic factors, in order to control for these factors in subsequent regression analyses. Significant relations were found for class status, X^2 (4, N = 422) = 111.83, $p < .001$, with a majority of students in the AL course (59%) being sophomores and a majority of students in the non-AL course (44%) being seniors, as well as cumulative GPA, X^2 (4, N = 420) = 12.40, $p < .05$. Class status and cumulative GPA were controlled for in subsequent regression analyses comparing the two courses.

A two stage hierarchical multiple regression was conducted with metacognitive self-regulation as the dependent variable. Preliminary analyses ensured that the assumptions of normality, linearity, and homoscedasticity were not violated. The correlation between the continuous predictor variables (cumulative GPA and theory of intelligence mean) was weak at $r = .12$, $p < 0.01$ (Table 1), indicating that multicollinearity was unlikely. Cumulative GPA, class status, and theory of intelligence mean were entered at stage one of the regression to control for factors outside of condition that affect metacognitive self-regulation. Condition was entered at stage two of the regression (Table 4), and explained an additional 1% of variation in anticipated final grade, $p < .05$. In the final adjusted model, theory of intelligence mean (β = .18, $p < 0.001$) and condition (β = .12, $p < 0.05$) were both significant.

Table 4. Hierarchical Regression Model predicting metacognitive self-regulation (N = 420)

	R	R^2	R^2 *Change*	*B*	*SE*	*β*	*t*
Step 1	.26	.07***					
Cum GPA				.15	.05	.15**	3.10
Class status				-.10	.05	-.10	-1.95
Theory of intelligence mean				.16	.05	.16**	3.24
Step 2	.28	.08*	.01*				
Cum GPA				.14	.05	.14**	2.82
Class status				-.06	.06	-.06	-1.13
Theory of intelligence mean				.18	.05	.18***	3.68
Condition				.25	.11	.12*	2.24

Note. Statistical significance: *p < .05; **p < .01; ***p < .001

Can student buy-in to AL pedagogies better predict engagement of metacognitive self-regulation than mere exposure to these pedagogies?

The relationships between buy-in to AL pedagogies and metacognitive self-regulation within the AL condition were examined. A two stage hierarchical multiple regression was conducted, again with metacognitive self-regulation as the dependent variable. Preliminary analyses ensured that the assumptions of normality, linearity, and homoscedasticity were not violated.

The correlations between the continuous predictor variables were weak, indicating that multicollinearity was not a concern (Table 5). Cumulative GPA, class status, and theory of intelligence mean were entered at stage one of the regression to control for factors outside of condition that affect metacognitive self-regulation. Buy-in score was entered at stage two of the regression (Table 6), and explained an additional 8% of variation in anticipated final grade, $p < .001$. In the final adjusted model only buy-in was a significant predictor of metacognitive self-regulation, $\beta = .29$, $p < 0.001$.

Table 5. Descriptive statistics, reliability, and correlations for all continuous variables within AL condition (N = 289)

Variables	M	CG	TOI	B
Metacognitive self-regulation mean (M)	1			
Cum GPA (CG)	..16**	1		
Theory of intelligence mean (TOI)	.17**	.23***	1	
Buy-in sum (B)	.33***	.11*	.21***	1
Means	5.04	3.12	4.09	34.75
Standard Deviations	1.04	.87	1.30	17.27
Range	1-7	1-5	1-6	1-78
Possible range	1-7	1-5	1-6	1-81
Cronbach's Alpha	.07	.11	.08	.39

Note. Statistical significance: *p < .05; **p < .01; ***p < .001

Table 6. Hierarchical Regression Model predicting metacognitive self-regulation within AL condition (N = 289)

	R	R^2	R^2 *Change*	*B*	*SE*	*β*	*t*
Step 1	.24	.06**					
Cum GPA				.11	.06	.10	1.69
Class status				-.16	.08	-.12*	-1.99
Theory of intelligence mean				.14	.06	.14*	2.36
Step 2	.37	.14	.08***				
Cum GPA				.10	.06	.09	1.57
Class status				-.11	.08	-.09	-1.50
Theory of intelligence mean				.08	.06	.08	1.43
Buy-in sum				.29	.06	.29***	5.10

Note. Statistical significance: *p < .05; **p < .01; ***p < .001

Discussion

Is there support for a learning pathway in which metacognitive self-regulation makes possible the employment of other adaptive learning strategies, allowing for greater achievement?

The initial mediational analysis indicated that adaptive learning strategies mean fully mediated the relationship between metacognitive self-regulation mean and anticipated final grade. This finding provides support for a theoretical model in which metacognitive self-regulation enables the usage of other adaptive learning strategies, including cognitive strategies (rehearsal, elaboration, organization, critical thinking) and resource management strategies (time and study environment, effort regulation, peer learning, help seeking). The results provide support for Corno's (1986) claim that metacognition plays a special role in learning, and justify prioritizing teaching strategies that specifically encourage the development of metacognitive self-regulation.

Can metacognition predict achievement independent of theory of intelligence?

Theory of intelligence and metacognitive self-regulation had a small combined effect on anticipated final grade when controlling for demographic factors and GPA. However, metacognitive self-regulation did have a significant effect independent of theory of intelligence. This effect indicates that pedagogical interventions that increase students' metacognitive self-regulation can impact course achievement without necessarily targeting students' theories of intelligence, providing evidence against the claim made by much of the existing literature that metacognition is caused by theory of intelligence and learning orientation.

Can the employment of active learning pedagogies by an instructor affect student engagement of metacognitive self-regulation, independent of theory of intelligence?

Controlling for demographic factors, GPA, and theory of intelligence, experimental condition had a small but significant effect on metacognitive self-regulation. This indicates that an active learning instructional style can result in a significant increase in a student's engagement of metacognitive self-regulation independent of other factors, which, as discussed earlier, can improve the student's course achievement. Anticipated final grades across courses were not directly compared because of differences in grading schemes.

Can student buy-in to active learning pedagogies better predict engagement of metacognition than mere exposure to these pedagogies?

Within the active learning condition, students' reported buy-in to active learning had a significant effect on metacognitive self-regulation independent of other factors. This effect indicates that it matters not just that students are exposed to active learning pedagogies, but also that they are persuaded by, identify with, and commit to them. Theory of intelligence is not significant in this model, suggesting that it is not a factor influencing the likelihood that a student will buy in to active learning. However, it remains to be seen what factors do influence buy-in. Nevertheless, this result reinforces Cavanagh et al.'s (2016) claim that instructors must remain cognizant of the extent to which students engage with active learning pedagogy, rather than blindly adopting new strategies. Furthermore, instructors must maintain awareness that buy-in will not be uniform across a group of students.

Implications

In recent years, the "growth mindset"—the equivalent of an incremental theory of intelligence and a learning goal orientation—has become a focus of pedagogical innovation (Dweck, 2015). Much of the existing literature presupposes that students' adaptive behaviors, including the use of metacognition, stem from their theories of intelligence and goal orientations (Landine & Stewart, 1998; Ford et al., 1998; Vrugt & Oort, 2007). The results of this study indicate that this may not be the case, however, and that teaching interventions can increase students' engagement of adaptive behaviors without the involvement of theory of intelligence. While interventions based on growth mindset can certainly improve student outcomes (O'Rourke et al., 2014; Yeager et al., 2016), it is erroneous to assume that this mindset is the foundation for the usage of adaptive learning strategies, in particular because the growth mindset is a more abstract construct that can often be invoked in the classroom without any concrete implementation (Dweck, 2015). A more holistic approach is necessary.

The results of this study indicate that active learning pedagogies can increase student engagement of metacognition, likely by exposing students to unique learning strategies and encouraging students to reflect on the personal effectiveness of these strategies (Vos & De Graaff, 2004). The results of the mediational analysis indicate that this increase in metacognition enables the usage of other adaptive learning strategies, thus leading to higher final grades.

Active learning pedagogy, in practice, is largely centered around the transmission of non-metacognitive adaptive learning strategies (Meyers & Jones, 1993; Silberman, 1996; Couch et al., 2015). Students gain practice in skills such as elaboration, organization, and peer learning through active learning exercises involving relating scientific knowledge to other disciplines, or through group work. However, given the central role of metacognition indicated by the results of this study, greater emphasis should be placed on the explicit teaching of metacognitive strategies, rather than allowing metacognition to be a side effect of exposure to varied learning techniques. Strategies for such metacognitive instruction include the "Muddiest Point," in which the instructor provides a few minutes at the end of each session for students to identify in writing the topic from that day's lecture that they found most confusing, or assigning students "reflective journal" exercises in which they respond to questions such as "What about my exam preparation worked well that I should remember to do next time? What did not work so well that I should not do next time or that I should change?” (Tanner, 2012).

Limitations

Analyses were based not on students’ actual final grades, but on anticipated final grades reported at the end of the term, and it is possible that these reported grades do not align with final grades. In particular, it may be the case that students’ predictions of their grades are influenced by demographic characteristics such as gender or URM status (Aronson et al., 2002; Spencer et al., 1999), or by other factors explored in the study such as theory of intelligence. Future studies should collect objective grade measures in order to prevent a potential skew introduced by self-reporting.

It is possible that a pre-existing difference between the two conditions in some unidentified factor is driving the effects observed in this study. Differences in GPA and class status between the two courses suggest that there may be some difference in personality between students in the two courses. However, the directionality of these differences—students in the non-AL control condition had, on average, a higher GPA and a higher class status than students in the AL experimental condition—make it unlikely that these factors can explain the difference in metacognitive self-regulation, which is in the opposite direction.

It is also possible that some unidentified pre-existing characteristic of the instructors’ teaching styles can explain the observed effects. It may be the case that there is some aspect of the active learning course instructor’s teaching style, unrelated to active learning pedagogy, that explains the difference in metacognitive self-regulation between the two conditions. These limitations may be addressed in future studies by having the same instructor teach two versions of the same course, one with an active learning teaching style and one without, to isolate the effect of pedagogy independent of overall instructional quality or content area.

Future Directions

In order to further establish the causal relationships between the factors explored in this study, longitudinal data should be collected to determine how the *change* in metacognitive self-regulation of students in active learning courses differs from the change in metacognitive self-regulation of students in non-active learning courses. This would involve collecting data prior to the start of the course, which was not done in this study. Furthermore, data should be collected from students not only immediately after the conclusion of the course, but also at some further time point down the line—perhaps at the end of the following semester—to determine whether exposure to an active learning teaching style can have lasting effects on metacognitive self-regulation.

While this study provided support for the claim that metacognitive self-regulation can predict course grade independent of theory of intelligence, persistence in scientific fields may be an outcome variable of greater interest since grading schemes can be so variable across courses. The collection of longitudinal data can therefore more directly address the question of whether pedagogies that increase student metacognition can increase persistence in STEM and decrease attrition.

Further research should also explore the question of whether the relationships observed in this study between instructional style, metacognition, and achievement translate to students in other age groups and fields. Are these effects exclusive to college undergraduates in the sciences, or do they hold across populations?

Finally, it is necessary to conduct research that examines the relationships between active learning pedagogies and student outcomes at a more granular level. While the present study used sum scores of both perceived pedagogical implementation by instructors and of personal strategy use, future research should examine the individual relationships between these variables. Understanding these specific relationships will allow for more targeted intervention. While the results of the present study indicate that, at a broad level, active learning pedagogy increases metacognition, it may be valuable to know, for example, that having students provide feedback to their peers increases their ability to recognize gaps in their own knowledge. By more tightly linking research and pedagogy, we can improve student experiences and learning—perhaps not exclusively in STEM but across disciplines.

Author Contributions

Graham was principal investigator for the National Science Foundation grant (NSF TUES #1323258) from which the present data was collected. Andrew Cavanagh, postdoctoral research associate on the project based at the Yale Center for Teaching & Learning (CTL), collected the data as part of an evaluation effort for the Summer Institutes for Scientific Teaching. Dorai defined the research questions explored in this paper and analyzed the data with theoretical guidance from Graham as well as Meghan Bathgate and Melanie Bauer, two researchers affiliated with the CTL. Graham provided feedback on an initial draft of the paper, which was revised by Dorai to produce the present version.

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Appendix A

Scientific Teaching Taxonomy (Couch et al., 2015)

1. I had learning goals for what I was expected to know and be able to do
2. I received feedback on my progress towards course objectives throughout the semester
3. I received exam grades that I did not understand
4. I provided feedback to my instructor on his or her teaching methods
5. I related scientific concepts to everyday experiences
6. I developed hypotheses and made predictions based on my hypotheses
7. I designed and/or conducted experiments
8. I completed exercises that led me to draw my own conclusions
9. I presented my scientific ideas in writing
10. I read and evaluated scientific literature or media articles
11. I completed in-class activities other than listening to a lecture
12. I listened to lecture presentations and took notes
13. I responded to short in-class writing prompts
14. I completed in-class activities in groups of two or more
15. I answered questions in class using a clicker or other polling method
16. I heard from members of the whole class about their group work
17. I worked in diverse groups

18. I considered the contributions of diverse people and perspectives
19. I used examples or analogies that included a diversity of people and cultures
20. I engaged in higher level thought processes that required me to apply my knowledge and skills
21. I memorized facts from the textbook
22. I applied knowledge of other subjects
23. I identified appropriate strategies for solving different types of problems
24. I reflected on the effectiveness of my study habits
25. I analyzed or interpreted scientific data shown in graphs or tables
26. I provided feedback to my classmates on projects, assessments, or other activities
27. I participated in open-ended exercises, such as case-studies or questions in which multiple correct answers are possible

Appendix B

Motivated Strategies for Learning Questionnaire, Metacognitive Self-Regulation subscale (Pintrich et al., 1991)

36. When reading for this course, I make up questions to help focus my reading.
41. When I become confused about something I'm reading for this class, I go back and try to figure it out.
44. If course materials are difficult to understand, I change the way I read the material.
61. I try to think through a topic and decide what I am supposed to learn from it rather than just reading it over when studying.

76. When studying for this course I try to determine which concepts I don't understand well.
78. When I study for this class, I set goals for myself in order to direct my activities in each study period.
79. If I get confused taking notes in class, I make sure I sort it out afterwards.

Appendix C

Motivated Strategies for Learning Questionnaire, Non-Metacognitive Adaptive Learning Strategies (Pintrich et al., 1991)

32. When I study the readings for this course, I outline the material to help me organize my thoughts.
35. I usually study in a place where I can concentrate on my course work.
38. I often find myself questioning things I hear or read in this course to decide if I find them convincing.
42. When I study for this course, I go through the readings and my class notes and try to find the most important ideas.
43. I make good use of my study time for this course.
52. I find it hard to stick to a study schedule. *(Reverse coded)*
62. I try to relate ideas in this subject to those in other courses whenever possible.
63. When I study for this course, I go over my class notes and make an outline of important concepts.
64. When reading for this class, I try to relate the material to what I already know.
65. I have a regular place set aside for studying.

66. I try to play around with ideas of my own related to what I am learning in this course.
67. When I study for this course, I write brief summaries of the main ideas from the readings and my class notes.
69. I try to understand the material in this class by making connections between the readings and the concepts from the lectures.
70. I make sure that I keep up with the weekly readings and assignments for this course.
71. Whenever I read or hear an assertion or conclusion in this class, I think about possible alternatives.
73. I attend this class regularly.
77. I often find that I don't spend very much time on this course because of other activities. *(Reverse coded)*
80. I rarely find time to review my notes or readings before an exam. *(Reverse coded)*
81. I try to apply ideas from course readings in other class activities such as lecture and discussion.

Appendix D

Supplemental tables for mediational analysis of metacognitive self-regulation, adaptive learning strategies, and anticipated final grade

Table 7. Hierarchical Regression Model of anticipated final grade based on metacognitive self-regulation (N = 418)

	R	R^2	R^2 *Change*	*B*	*SE*	*β*	*t*
Step 1	.59	.35***					
URM Status				.03	.10	.01	.26
Gender				-.25	.08	-.13**	-3.22
Cum GPA				.57	.04	.57***	13.89
Step 2	.60	.36***	.01**				
URM Status				.01	.10	.01	.13
Gender				-.25	.08	-.13**	-3.23
Cum GPA				.55	.04	.55***	13.18
Metacognitive self-regulation mean				.11	.04	.11**	2.71

Note. Statistical significance: *p < .05; **p < .01; ***p < .001

Table 8. Hierarchical Regression Model of adaptive learning strategies based on metacognitive self-regulation (N = 420)

	R	R^2	R^2 *Change*	*B*	*SE*	*β*	*t*
Step 1	.21	.04***					
URM Status				.19	.12	.08	1.56
Gender				.14	.10	.07	1.45
Cum GPA				.20	.05	.20***	4.05
Step 2	.80	.64***	.64***				
URM Status				.09	.07	.04	1.23
Gender				.14	.06	.07*	2.46
Cum GPA				.04	.03	.04	1.29
Metacognitive self-regulation mean				.79	.03	.79***	26.12

Note. Statistical significance: *p < .05; **p < .01; ***p < .001

Table 9. Hierarchical Regression Model of anticipated final grade based on adaptive learning strategies (N = 419)

	R	R^2	R^2 *Change*	B	SE	β	t
Step 1	.59	.35***					
URM Status				.03	.10	.01	.26
Gender				-.25	.08	-.13**	-3.22
Cum GPA				.57	.04	.57***	13.89
Step 2	.61	.37***	.02***				
URM Status				.00	.10	.00	-.01
Gender				-.27	.08	-.14***	-3.51
Cum GPA				.54	.04	.54***	13.12
Adaptive learning strategies mean				.15	.04	.15***	3.62

Note. Statistical significance: *p < .05; **p < .01; ***p < .001