LEARNING STRATEGIES FOR MATH GROWTH MINDSET, SELF-REGULATION AND PERFORMANCE

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This study examines the effectiveness of integrating learning-strategy instruction within the content of gate-keeper math courses in fostering a math growth mindset and self-regulated learning (SRL) in underrepresented minority students and its implications on students' performance. We propose and explore innovative ways to seamlessly integrate evidence-based cognitive, metacognitive, and management learning strategies within the course via the presentation of course material, class discussions, and assignments. Our conceptual framework provides a model for understanding the interrelationships between four constructs: learning strategies, math mindset, SRL, and performance, while accounting for the students' racial, gender, and math identities.

Introductory mathematics courses are the cornerstone courses for STEM disciplines. They provide students with the quantitative training needed for their STEM majors, all of which are becoming more quantitative in response to a rapidly changing data-driven job market. Students' performance in these foundational math courses profoundly impacts their transitions from high school to college, their ability to remain enrolled, make progress, and ultimately graduate (Carver et al., 2017). Nonetheless, enhancing students' learning experiences and achievements in these critical gateway courses has posed a persistent challenge for higher education institutions throughout the country. This challenge is even more pronounced for minority-serving institutions, including Historically Black Colleges and Universities (HBCUs).

Extensive research has explored the influence of math growth mindset and self-regulated learning (SRL) on the academic performance and persistence of STEM students (e.g., Yeager et al., 2019). Similarly, a wealth of literature highlights the positive correlations between learning strategies and SRL, as well as the link between instruction in learning strategies and enhanced academic performance (Donker et al., 2014; Weinstein et al., 2000). The majority of these investigations have centered on K-12 students. As a result, there is a notable gap in knowledge concerning the effectiveness of innovative approaches to integrate learning-strategy instruction within math courses, with the aim of fostering a math growth mindset and SRL among HBCU students. Furthermore, it remains unclear whether math growth mindset, SRL, or a combination of both, function as mediating factors in the relationship between learning-strategy instruction and the performance of HBCU students in math courses.

The present study explores innovative ways to seamlessly integrate evidence-based cognitive, metacognitive, and management learning strategies within four gate-keeper math courses (College Algebra I/II and Calculus I/II) via the presentation of course material, class discussions, and assignments. Data is collected to evaluate the efficacy of learning-strategy instruction in fostering a math growth mindset and SRL in underrepresented minority students and its implications on students' performance in these courses. The research is well-timed, as the demand for knowledge and application of learning strategies, fostering a growth mindset, and embracing SRL is paramount for academic success in the post-COVID era.

Related Literature and Framework

The belief that math ability is inherent has been ingrained in the U.S. (Stevenson et al., 1993). This belief constitutes a fixed mindset and contributes to the persistent problem of underachievement and low participation in math (Boaler, 2013), especially among females, African Americans, and Latinx students (Flores, 2007; Sun, 2015). On the contrary, growth mindset is the belief that intelligence can be increased through one's efforts (Dweck, 2000, p.3).

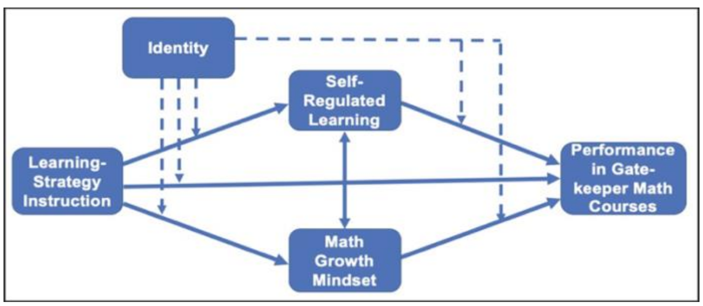
Another factor influencing students' math performance is whether they employ SRL (e.g., Fauzi & Widjajanti, 2018). Self-regulated learners are characterized by their ability to be metacognitively, motivationally, and behaviorally active participants in their own learning process (Zimmerman, 2000). They are actively involved in maximizing their opportunities and abilities to learn and can critically evaluate and intentionally alter how their thoughts, behaviors, and working environments contribute to their learning outcomes (Darr & Fisher, 2015). Self-regulation is also crucial for mathematical problem-solving (Marchis, 2012).

According to literature, students' knowledge and use of learning strategies can be a common facilitator of both constructs of math growth mindset and SRL, which would in turn lead to improvements in students' performance in math. Learning strategies, as defined by Pressley et al. (1989), refer to "processes (or sequences of processes) that, when aligned with the requirements of tasks, enhance performance." These strategies encompass students' thoughts, behaviors, or beliefs that facilitate the acquisition, comprehension, or practical application of new knowledge and skills (Weinstein et al., 2000).

Our proposed conceptual framework is poised to serve as a model for future research examining the intricate connections among instructional strategies for learning, the development of a math growth mindset, SRL, and math performance. This framework postulates the following hypotheses: (i) learning-strategy instruction has a direct effect on students' performance (Donker et al., 2014); (ii) learning-strategy instruction can indirectly influence performance by fostering students' math growth mindset, leading them to perceive new avenues for growth in learning and achievement, and students' SRL (McDaniel & Einstein, 2020); (iii) a bidirectional association exists between math growth mindset and SRL; and (iv) students' various social identities (such as racial, gender, and math identities) are likely to moderate the relationships described in (i)-(iii). The bidirectional relationship in (iii) has not been tested in the literature and is motivated by the results of Burnette et al. (2014) who concluded that the associations between mindsets and self-regulation are not straightforward.

Fig 1

Conceptual Framework.



Guided by the above framework, the study will address the following research questions.

Table 1

Research Questions.

RQ1	To what extent does learning-strategy instruction in gate-keeper courses promote math growth mindset?
RQ2	To what extent does learning-strategy instruction in gate-keeper math courses promote SRL?
RQ3	What is the nature of the association between students' math growth mindset and SRL? When and how is math growth mindset consequential for SRL and vice versa?
RQ4	To what extent do learning-strategy instruction, math growth mindset, and SRL predict students' performance in gate-keeper math courses?

Methodology

Intervention

We used various types of activities to inherently integrate learning strategies within four gate-keeper math courses to promote math growth mindset and SRL simultaneously. We focused on four key learning strategies: Elaboration (cognitive), Self-testing and Adaptation of Learning Approach (metacognitive), and Effort Management (management). As found by Donker et al. (2014), elaboration strategies can be effective for learning math as they help students form internal connections between existing knowledge and new material. Instructors can train students to use elaboration strategies by encouraging student explanation, sense-making, and justification using class discussions and discussion board assignments. Such discussions allow students to form a math growth mindset (e.g., Sun, 2015, p.37) and directly connect to the self-reflection phase of Zimmerman's SRL model (Zimmerman, 2000). Self-testing and adaption of learning approach strategies are two learning strategies that connect with both math growth mindset and SRL. By frequently encouraging self-testing and allowing for multiple attempts, instructors can help students develop a math growth mindset (e.g., Sun, 2015) and allow them to practice self-monitoring (the performance phase of SRL). Presenting mathematical tasks that allow for multiple solutions sends growth mindset messages and motivates students to adjust their learning strategies for better task performance (the self-reflection phase of SRL). Finally, instructors who frequently make effort attributions about math tasks encourage students to practice effort management strategies (forethought phase of SRL) and promote math growth mindset. Students were exposed to these learning strategies via a series of discussion board assignments followed by online and in-class reflections. For example, in week three students were assigned to watch a video about the study cycle and make a post and at least one reply in the discussion forum about it. In the following week, the study cycle was demonstrated by the instructor in the context of the math course and connections were made with the students' discussions from the online forum.

Study Design

The study utilizes a repeated-measures between-subjects design where four sections in each of the four target math courses (College Algebra I/II and Calculus I/II) at a large HBCU were assigned to a treatment group (2 sections) or a control group (2 sections). *Treatment* students were taught about effective math learning strategies including elaboration, self-testing, effort and time management, and test-taking strategies in the form of class discussions and activities, discussion board assignments, and short videos and quizzes. *Control* students, on the other hand, were taught the same course content without any instruction on learning strategies.

Data and Scales

To evaluate the effectiveness of integrating learning strategies into gatekeeper math courses, we use data collected during the 2022-2023 academic year from students at the study institution. The data comes from 32 sections (16 treatment and 16 control) spanning four introductory math courses. The data consists of i) students' responses to pre- and post-surveys about their math mindset, SRL, and math, gender, and racial identities; ii) students' scores on pre- and post-tests related to course content, and iii) students' demographic (gender, PELL status, and residency) and academic (STEM status, classification, and GPA) characteristics. A total of 986 students (502 control and 484 treatment) completed the pre- and post-content tests and 551 students (278 control and 273 treatment) completed the pre- and post-surveys.

Hocker's (2017) modified math mindset scale was adapted and used for measuring students' math mindsets. The Self-Regulation Strategy Inventory–Self-Report, developed by Cleary (2006), was used to measure students' SRL. The original SRL scale, validated on a sample of high school students, had three subscales: (a) Managing Environment and Behavior, (b) Maladaptive Regulatory Behaviors, and (c) Seeking and Learning Information. Racial identity was measured using Sellers et al.'s (1997) Multidimensional Inventory of Black Identity (MIBI) for Black students and Brown et al.'s (2014) Multigroup Ethnic Identity Measure for non-Black students. Gender identity was measured using a modified version of the MIBI scale. Finally, math identity was measured using Lock et al.'s (2013) math identity scale which consists of three subscales: (a) math competency, (b) math recognition, and (c) math interest.

Statistical Analysis

The data analysis included descriptive statistics, psychometric analyses of the mindset, SRL, and various identity scales, correlations, and regression modeling. All analyses were conducted using the open-source statistical software R version 4.1.3. A 5% significance level is used.

Results

The statistics in Table 2 show reasonable similarity between students in the control and treatment sections in terms of their background characteristics.

Table 2

Characteristics of the sample participants by their role in the study.

Variable	Control: n (%)	Treatment: n (%)
Gender: Female	152 (65.52%)	162 (71.78%)
STEM: Yes	128 (55.17%)	100 (44.25%)

Variable	Control: n (%)	Treatment: n (%)
PELL: Yes	208 (89.66%)	199 (88.05%)
Residency: Out-of-State	121 (52.16%)	105 (46.46%)
GPA: >= 3.00	93 (56.71%)	107 (68.15%)

The psychometric analysis, consisting of both exploratory and confirmatory factor analyses, of the mindset items showed a good fit for the mindset scale to the data: root mean square of the residuals (RMSR) = .002 for pre-survey & .001 for post-survey. On the other hand, the SRL items did not fit the original three-factor structure with the items of the Seeking and Learning Information subscale not loading on a single factor as hypothesized. The two-factor structure provided an acceptable fit with the Managing Environment and Behavior and the Maladaptive Regulatory Behaviors subscales forming two separate factors (presurvey RMSR = .056 & post-survey = .057). These two subscales, labeled *SRL-1* and *SRL-2*, did not load on a common higher -order factor (pre-survey factor cor. = -.03 & post-survey = -.18) and were analyzed separately.

Table 3

Estimates of regression coefficients (standard errors) from four regression models with the response variable shown in the column and explanatory variables shown in the rows.

Explanatory Variable	Mindset Diff	SRL-1Diff	SRL-2 Diff	Performance Diff
	Estimate (S.E.)	Estimate (S.E.)	Estimate (S.E.)	Estimate (S.E.)
Role: Treatment	0.180 (0.106) ·	0.023 (0.058)	-0.083 (0.074)	-3.924 (2.418)
Mindset Difference	-	-0.003 (0.032)	0.155 (0.040) ***	2.834 (1.348) *
SRL-1 Difference	-0.010 (0.107)	-	0.172 (0.074) *	3.281 (2.414)
SRL-2 Difference	0.319 (0.082) ***	0.107 (0.046) *	-	4.438 (1.891) *
Gen Identity Reflection	-0.100 (0.046) *	0.058 (0.025) *	-0.003 (0.032)	0.588 (1.070)
Gen Identity Centrality	0.069 (0.045)	-0.008 (0.025)	0.042 (0.032)	0.503 (1.028)
Racial Identity	0.173 (0.073) *	-0.028 (0.040)	-0.050 (0.051)	-1.932 (1.665)
Math Iden: Competency	0.063 (0.115)	-0.068 (0.063)	-0.121 (0.080)	3.265 (2.619)
Math Iden: Recognition	0.148 (0.072) *	0.013 (0.400)	-0.023 (0.050)	1.524 (1.171)
Math Iden: Interest	-0.178 (0.016) **	0.000 (0.034)	0.093 (0.043) *	-1.450 (1.429)
Gender: Male	0.136 (0.126)	0.046 (0.069)	-0.042 (0.088)	-5.338 (2.880) ·
STEM: Yes	-0.120 (0.125)	-0.053 (0.069)	-0.040 (0.087)	-1.983 (2.861)
GPA	0.014 (0.089)	0.034 (0.049)	-0.009 (0.062)	1.456 (2.003)
PELL: Yes	0.243 (0.178)	0.165 (0.098) ·	-0.090 (0.124)	1.462 (3.665)
Residency: Out-of-State	0.052 (0.110)	-0.031 (0.060)	0.059 (0.076)	-0.699 (2.498)
Class: Sophomore	-0.012 (0.116)	0.004 (0.064)	-0.118 (0.081)	-0.432 (2.646)
Class: Junior	-0.282 (0.242)	0.062 (0.133)	0.166 (0.169)	-4.430 (5.683)
Class: Senior	-0.506 (0.940)	-1.115 (0.513) *	-0.360 (0.655)	-7.612 (20.76)
Course: Algebra II	-0.111 (0.138)	0.021 (0.076)	0.043 (0.096)	8.757 (3.097) **
Course: Calc I	0.081 (0.166)	0.102 (0.091)	0.003 (0.115)	-8.352 (3.765) *
Course: Calc II	-0.003 (0.181)	0.040 (0.099)	0.313 (0.125) *	18.017 (4.166) ***
Adjusted R^2	0.078	0.014	0.088	0.212

Note: Reference category is "Control" for *Role*, "Female" for *Gender*, "No" for *STEM* and *PELL*, "In-State" for *Residency*, "Freshman" for *Classification*, and "Algebra I" for *Course*.
Significance codes: '***' ≡ p-value < .001; '**' ≡ p-value < .01; '*' ≡ p-value < .05; '·' ≡ p-value < .1

Several regression models were developed to investigate research questions **RQ1**, **RQ2**, and **RQ4**. The results are summarized in Table 3 where the response variables represented the change in math mindset (*posttest score – pretest score*), the change in *SRL-1* and *SRL-2*, and the change in performance on the content tests. These results suggest that 1) accounting for students' SRL, identities, background characteristics, and course, learning-strategy instruction was associated with positive, yet marginal (coef. = 0.18, p =.090), improvement in math growth mindset; 2) accounting for students' math mindset, identities, background characteristics, and course, learning-strategy instruction was not significantly associated with changes in SRL; 3) both gains in math mindset and gains in *SRL-2* were positively associated with gains in students' performance on the content tests (*Mindset*: coef. = 2.83, p = .036; *SRL-2*: coef. = 4.44, p = .020) but learning-strategy instruction was not significantly associated with performance gains.

Correlation analyses were conducted to test the bidirectional association in **RQ3**. The bivariate Pearson correlation analysis between students' math mindset scores and SRL scores showed that 1) students' initial mindset and SRL scores were moderately correlated with their post-semester mindset and SRL scores (*Mindset*: cor. = .53, 95% CI [.47, .59], $p < .001$; *SRL-1*: cor. = .69, 95% CI [.64, .73], $p < .001$; *SRL-2*: cor. = .50, 95% CI [.44, .56], $p < .001$), and 2) students' post-semester *mindset* scores had weak positive correlation with their initial *SRL-2* scores (cor. = .36, 95% CI [.28, .43], $p < .001$) but were not significantly correlated with their initial *SRL-1* scores (cor. = -.02, 95% CI [-.10, .07], $p > .999$). Additionally, the cross-lagged correlation analysis revealed that 1) students' initial math mindset was not predictive of their end-of-semester SRL (*SRL-1*: coef. = 0.004, p = .872; *SRL-2*: coef. = 0.04, p = .175) given their pre-semester SRL score, and 2) only students' initial *SRL-2* was predictive of their end-of-semester math mindset (coef. = 0.29, $p < .001$) given their pre-semester math mindset. These results suggest a unidirectional relationship between math mindset and SRL.

Concluding Remarks

The results reported in this study are preliminary results from one phase of data collection. We will continue to refine these results using data from additional data collection phases and revised analysis plans. For instance, we will apply the retrospective pretest-posttest (RPP) design (e.g., Little et al., 2019) using data from the 2023-2024 academic year and contrast the results with the traditional pretest-posttest design. The RPP design allows participants to gauge the degree of change that they experience with greater awareness and precision by asking respondents to rate survey items twice during the same posttest measurement occasion from two specific frames of reference: “now” and “at the start of the semester.” Furthermore, future phases of analyses will account for additional factors such as instructor and class attendance.

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