Technology-Based Instructional Strategies Show Promise in Improving Self-Regulated Learning Skills at Broad-Access Postsecondary Institutions

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ABSTRACT

Self-regulated learning (SRL) is critical for student success in online postsecondary education. Many technology-based interventions have been studied to improve SRL skills, but few were situated in broad-access institutions that disproportionately serve systemically marginalized student populations in STEM fields. This study presents preliminary findings from a rapid-cycle evaluation that tests two technology-supported instructional strategies (videos and prompts) designed to improve SRL in online learning. Using fine-grained clickstream data from 141 students across ten sections of five courses taught at a minority-serving community college, we generate measures of SRL behavior and correlate them with students' exposure to tested strategies. Our results indicate modestly positive relationships between both videos and prompts and SRL behavior. In addition, prompts are more strongly correlated with SRL behavior for first-generation and female students than for their peers. These initial findings reveal the promise and complexity of implementing effective and equitable technology-supported interventions to develop SRL skills and mindsets among diverse student populations in online STEM education.

CCS CONCEPTS

• **Applied computing** → **Learning management systems**; **E-learning**; **Distance learning**; **Computer-assisted instruction**; • **Information systems** → *Data stream mining*; • **Human-centered computing** → *Empirical studies in HCI*.

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KEYWORDS

Postsecondary Education; Self-Regulated Learning; Online Learning; Educational Technology; Learning Analytics; Learning Management System; Educational Equity

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1 INTRODUCTION

Online learning has seen a rapid growth in postsecondary education in the past decade, especially with the long-run impacts of the COVID-19 pandemic. As of Fall 2021, 61% of all undergraduate students in the United States enrolled in at least one online course and 28% enrolled in online courses exclusively [7]. In online environments, college students must manage their studies more independently than in traditional classrooms. Therefore, improving self-regulated learning (SRL) skills is a critical undertaking for educators who aim to support student success in online learning [13]. This effort is particularly vital at broad-access institutions, which not only enroll the largest share of postsecondary students but also serve a diverse population often balancing employment, family duties, and educational commitments. Moreover, these institutions face pronounced socioeconomic disparities in online learning outcomes [11].

This paper is situated in a larger collaborative initiative to study technology-based instructional strategies to help students develop SRL skills and succeed in online STEM courses. The initiative engages nine broad-access institutions across the United States. As part of the initiative, instructors participate in the rapid-cycle evaluation (RCE) to test in their courses one or more technology-based instructional strategies designed to promote students' SRL skills.

Multiple data sources are collected by the research team to understand the promise of tested strategies and inform the development of a holistic instructional model for developing SRL skills in online STEM courses. As an early examination of RCEs, we leverage students' online behavioral traces to examine the relationship between two instructional strategies – three-part video series and prompts – and students' SRL behavior. These strategies were implemented at one partner institution in the first two iterations of the RCE. More importantly, we evaluate how this relationship differs across student populations, shedding light on the equity implications of the tested strategies.

2 RELATED WORK

Self-regulated learning (SRL) is a critical success factor in online and postsecondary education, given that learners are often expected to work independently and exert control over their own learning journey, unlike in traditional classroom and K-12 settings. Empirical evidence has suggested a positive relationship between SRL and online learning outcomes, such as academic performance, satisfaction, and persistence (e.g., [5, 6]).

Educational and psychological researchers have characterized SRL as a multifaceted psychological process, including components like time management, metacognition, and effort regulation [2, 13]. Earlier research has established psychological scales to capture these components [1, 9], and the advent of digital learning platforms makes learning analytics a promising tool to depict SRL processes with granular learning behavior [8]. Importantly, analytics-based characterization of SRL has the advantage of being non-intrusive and easily scalable.

To support the development of SRL skills, a plethora of instructional interventions have been studied, such as online training modules, prompts, self-assessment, and peer support opportunities. Many of these interventions are supported by modern technologies [10], but marginalized and non-traditional learners can face barriers in reaping the benefits of these interventions due to factors such as reliable technology access and personalized support [4]. In addition, existing interventions are more often conducted in well-resourced educational settings with less urgent need of SRL capacity building. For example, broad-access postsecondary institutions, which serve disproportionately learners from historically marginalized populations and offer more online courses, are significantly understudied [12].

3 RESEARCH CONTEXT

The Postsecondary Teaching with Technology Collaborative[1] is a research, development, and capacity-building center that studies technology-enabled instructional strategies to support SRL in online courses. As a key part of the Collaborative, the rapid-cycle evaluation (RCE) iteratively tests a series of evidence-based strategies in collaboration with STEM instructors at broad-access institutions across three semesters (waves). In this paper, we evaluate two strategies tested in the first two semesters (Fall 2022 and Spring 2023). **Three-part video series** (**videos** for short) include short videos designed by educational researchers in collaboration with instructors. Each video consists of an overview of SRL, introduction to a key SRL skill/mindset (e.g., sense of belonging, time management), a handful of strategies to develop the skill/mindset, and an activity for students to reflect on their own practices and mindsets. **Prompts** are short-answer questions related to planning for the upcoming week, monitoring one's progress, and reflecting on one's own understanding of course concepts. Both strategies are expected to help students develop their SRL skills. The materials and suggested timeline for administering these strategies are provided to participating instructors, who are encouraged to make adaptations according to their own course contexts.

We empirically examine both strategies tested at one partner institution, which is a broad-access community college and designated Minority Serving Institution (MSI) in the northeastern region of the US. Across the two semesters, three instructors participated in RCE. Each participating instructor taught multiple parallel sections of one or more fully online STEM courses. Within each course, the instructor chose one or more sections to administer one or both instructional strategies and the remaining sections to serve as the comparison. Below, we use "section" to refer to parallel course sections, and "block" to refer to a course, which includes both intervention and comparison sections.

In this work, we examine students' SRL skills manifested through their online behavior. Most participating instructors used Moodle learning management system (LMS) as their main venue for organizing instructional materials and activities, so we obtained fine-grained clickstream data from Moodle. The data includes timestamped records of user behavior generated by students aged 18 and older who enrolled in the participating blocks and whose data we had research permissions to collect. Each clickstream record documents a user action with timestamp in the LMS course space as well as the nature of this action. We joined the clickstream data with administrative records to get students' background information and remove sections that did not actively use LMS and students who did not complete the course. The final dataset for analysis contains 231,462 actions performed by 141 students across 10 sections within 5 blocks.

4 METHODS

To understand the relationship between tested instructional strategies and students' SRL processes, we first attempt to quantify students' SRL behavior based on the clickstream data. We adapted a recent review of digital trace-based SRL measures [3] and constructed a set of SRL behavioral measures based on our dataset. These measures are shown in Table 1. By definition, an increase in each measure indicates improvement in the associated SRL component, except for `AvgSeshGap` which is defined in the opposite direction. After removing actions associated with the tested strategies themselves (videos and prompts) for students in the intervention sections, we calculated each SRL measure on a weekly basis for each student in each section (both intervention and comparison).

We then run the following two-way fixed effects model to estimate the average relationship between exposure to each tested strategy and SRL behavior:

$$Y_{ibst} = \alpha + \sum_{l} \gamma_l PostInt_{lst} + X_i + \pi_t + \lambda_b + \epsilon_{ibst} \tag{1}$$

[1] https://postseccollab.org/

SRL process	SRL subprocess	Measure (variable name)	Definition
Preparatory	Strategic planning	Action count: course info (CrsInfoActCnt)	# actions related to course information
Performance	Effort regulation	Action count: learning content (LrnActCnt)	# actions related to learning content
		Study session count (SeshCnt)	# study sessions
	Evaluation	Action count: assessment (AsmtActCnt)	# actions related to assessments
	Persistence	Average session duration (AvgSeshDur)	Average duration (in minutes) of study sessions
	Time management	Active day count (DayCnt)	# days with actions
		Average session gap (AvgSeshGap)	Average gap between two consecutive study sessions (in minutes)
Appraisal	Reflection	Action count: feedback (FdbkActCnt)	# actions related to feedback

Table 1: Measures of SRL behavior

where Y_{ibsk} is student i's SRL behavior in section s within block b in the t-th week of the academic term; $PostIntis_{lst}$ is a binary indicator of whether students in section s were already exposed to the lth strategy (video or prompt) in the tth week; π_t and λ_b are week and block fixed effects, respectively; X_i is a series of student-level control variables, such as demographics; ϵ_{ibst} is an idiosyncratic error term. The coefficient estimates $\tilde{\gamma}_l$ capture the average relationship between exposure to the lth strategy and SRL behavior.

To understand whether and how these relationships differ across subgroups of student, we identify ten subgroups to compare in pairs: females vs. males, underrepresented racial minorities (URM) vs. non-URM[2], first-generation vs. continuing-generation college students, Pell Grant recipients vs. non-Pell recipients, and part-time vs. full-time students. The first four pairs characterize systematically marginalized student populations in STEM fields versus their peers. We loop through the five pairs and in each loop add to Equation (1) interaction terms between each indicator of tested strategies ($PostInt_{lst}$) with the indicator of the marginalized subgroup (e.g., URM). If a student is missing information on one subgroup indicator, we remove them from the corresponding pairwise comparison.

Before running all the analyses above, we calculated each student's total duration of all actions in each section and removed outliers using the interquartile range (IQR) method.

5 RESULTS

Table 2 presents the standardized coefficients of exposure to videos and prompts ($\tilde{\gamma}_l$) from Equation (1). These estimates indicate an overall positive relationship between both videos and prompts and students' SRL behavior. Most prominently, exposure to both strategies is strongly correlated with increased actions related to course information (0.35 SD for videos and 0.42 SD for prompts). In addition, exposure to prompts is strongly associated with increased assessment-related actions (0.44 SD) and exposure to videos is strongly correlated with increased learning content actions (0.21

	Video	Prompt
CrsInfoActCnt	0.35*	0.42**
	(0.14)	(0.13)
LrnActCnt	0.21*	0.00
	(0.10)	(0.07)
SeshCnt	0.10	0.12
	(0.12)	(0.13)
AsmtActCnt	0.09	0.44***
	(0.09)	(0.08)
AvgSeshDur	0.06	0.08
	(0.07)	(0.06)
DayCnt	0.08	0.11
	(0.12)	(0.12)
AvgSeshGap	-0.09	-0.02
	(0.07)	(0.07)
FdbkActCnt	0.16	0.21
	(0.14)	(0.15)

Table 2: Estimated relationships between exposure to each tested instructional strategy and students' SRL behavior. Each row reports standardized estimated coefficients of exposure to videos and prompts from a separate regression model specified by Eq. (1), with standard errors in parentheses. $p < 0.05$ (*), $p < 0.01$ (**), $p < 0.001$ (***).

[2]Following postsecondary education research and existing routines in institutional reporting, we define URM status based on students' racial/ethnic categories. URM includes Black, Latine, Native American, and multi-racial, whereas non-URM includes white and Asian/Pacific Islander.

SD). Tying these results to the theoretical mapping in Table 1, videos seem to have the potential to improve strategic planning and, to a lesser extent, effort regulation. Prompts, on the other hand, can potentially improve strategic planning and evaluation.

In the subgroup analyses, we find that across six out of the eight SRL measures, exposure to prompts has a significantly stronger relationship with first-generation college students' SRL improvement compared to their peers. Similar patterns are also observed for female vs. male students in most dimensions of SRL, although the gender differences in the relationships are less pronounced. These results suggest that prompts may help develop SRL skills in an equitable manner because certain marginalized student populations in STEM fields may have experienced more growth in SRL than their counterparts from exposure to prompts.

6 DISCUSSION

This preliminary study examines two technology-based instructional strategies (videos and prompts) that were field-tested across 5 online STEM courses offered at a minority-serving community college. We find modestly positive relationships between exposure to both strategies and higher intensity of SRL behavior, especially in the preparatory phase. In addition, the positive relationships between exposure to prompts and different dimensions of SRL are stronger for certain systemically marginalized student populations compared to their peers.

Our results resonate with existing literature on SRL-promoting interventions particularly in online postsecondary education. The especially strong relationship between the tested strategies and the preparatory phase of SRL may suggest that students are mostly forward-looking and preparing for the future, compared to looking back, when navigating through tasks in sequence within a course. This merits further investigation to better understand the value of strategies specifically targeting planning behavior, and how other dimensions of SRL can be effectively supported. The observations that systemically marginalized students in STEM fields may have reaped more SRL gains from exposure to prompts are encouraging but deserve more thorough investigation of how the tested strategies might work differently for diverse student populations. Overall, our findings signal the potential to build these technology-based strategies into a comprehensive instructional model that supports equitable student success in online learning via developing SRL skills, but continued refinement and evaluation of these strategies are imperative to realize their full potential.

Our next steps include expanding the analyses to additional data sources, partner institutions, and iterations of RCE. We will also characterize SRL processes with more nuanced behavioral patterns to better evaluate the mechanisms of the tested strategies. Eventually, we aim to develop a deeper understanding of technology-supported interventions that effectively help students from marginalized backgrounds develop SRL skills and mindsets in online STEM education, and inform capacity building efforts at both instructional and institutional levels, both in our collaborative initiative and beyond.

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REFERENCES

[1] Rachel Baker, Di Xu, Jihyun Park, Renzhe Yu, Qiujie Li, Bianca Cung, Christian Fischer, Fernando Rodriguez, Mark Warschauer, and Padhraic Smyth. 2020. The benefits and caveats of using clickstream data to understand student self-regulatory behaviors: opening the black box of learning processes. *International Journal of Educational Technology in Higher Education* 17 (12 2020). Issue 1.

[2] J. Broadbent and W.L. Poon. 2015. Self-regulated learning strategies & academic achievement in online higher education learning environments: A systematic review. *The Internet and Higher Education* 27 (10 2015), 1–13.

[3] Jiahui Du, Khe Foon Hew, and Lejia Liu. 2023. What can online traces tell us about students' self-regulated learning? A systematic review of online trace data analysis. *Computers & Education* 201 (8 2023), 104828.

[4] Helen Jossberger, Saskia Brand-Gruwel, Henny Boshuizen, and Margje van de Wiel. 2010. The challenge of self-directed and self-regulated learning in vocational education: a theoretical analysis and synthesis of requirements. *Journal of Vocational Education & Training* 62, 4 (2010), 415–440.

[5] René F Kizilcec, Mar Pérez-Sanagustín, and Jorge J Maldonado. 2017. Self-regulated learning strategies predict learner behavior and goal attainment in Massive Open Online Courses. *Computers & Education* 104 (2017), 18–33.

[6] R. Lynch and M. Dembo. 2004. The Relationship Between Self-Regulation and Online Learning in a Blended Learning Context. *The International Review of Research in Open and Distributed Learning* 5, 2 (2004).

[7] U.S. Department of Education, National Center for Education Statistics. 2022. Digest of Education Statistics.

[8] Philip Winne. 2022. Learning Analytics for Self-Regulated Learning. In *The Handbook of Learning Analytics* (2nd ed.), Charles Lang, George Siemens, Alyssa Friend Wise, and Dragan Gaševic (Eds.). SoLAR, 78–85.

[9] Philip H Winne and Nancy E Perry. 2000. Measuring self-regulated learning. In *Handbook of self-regulation*. Elsevier, 531–566.

[10] Jacqueline Wong, Martine Baars, Dan Davis, Tim Van Der Zee, Geert-Jan Houben, and Fred Paas. 2019. Supporting self-regulated learning in online learning environments and MOOCs: A systematic review. *International Journal of Human–Computer Interaction* 35, 4-5 (2019), 356–373.

[11] Di Xu and Shanna S. Jaggars. 2014. Performance Gaps Between Online and Face-to-Face Courses: Differences Across Types of Students and Academic Subject Areas. *The Journal of Higher Education* 85 (2014), 633–659. Issue 5.

[12] Louise Yarnall, Rebecca Griffiths, and Hannah Cheever. 2023. *Teaching and Designing Online STEM Courses to Support Self-Directed Learning Skills.* Technical Report. SRI International.

[13] Barry J. Zimmerman. 2002. Becoming a self-regulated learner: An overview. *Theory into Practice* 41, 2 (2002), 64–70.