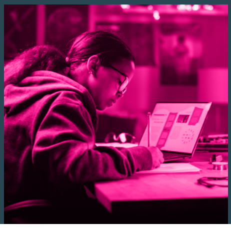
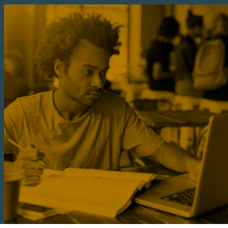
Self-Directed Learning Profiles and the Influence of Technology-Based Interventions Among STEM Undergraduates





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Abstract

As online STEM course enrollment continues to grow, challenges such as high dropout rates and reduced engagement persist, particularly among students from historically marginalized groups. Self-directed learning (SDL), which encompasses motivation, metacognition, and applied learning strategies, is critical for student success in these environments. This study identifies SDL profiles among 1,516 undergraduates enrolled in online STEM courses across four broad-access institutions and examines the impact of technology-based interventions—prompts, videos, and peer interaction activities—on students' likelihood of belonging to each profile over time. Using model-based clustering, we identified three distinct SDL profiles: (1) high self-regulation, (2) low confidence but high vigilance around studying, and (3) lower self-reported SDL skills. Multilevel models revealed that demographic and academic characteristics, such as race/ethnicity, enrollment status, and Pell eligibility, significantly predicted cluster membership. Over time, students in the intervention group showed greater increases in membership probability for Cluster 1, indicating the effectiveness of embedded SDL strategies. Cluster 3 membership declined overall but not because of the intervention, while Cluster 2 remained stable. These findings highlight the value of a person-centered approach to SDL and suggest that technology-integrated supports can promote adaptive learning behaviors and equity in online STEM learning environments.

Introduction and Theoretical Framework

The COVID-19 pandemic marked a pivotal moment in education, catalyzing a widespread shift to virtual learning. Since then, the number of college students enrolling in online courses has significantly increased. In the United States, the proportion of undergraduates taking at least one online course rose from 37% before the pandemic to 75% in 2020 and 60% in 2021, and remained relatively high at 54% in 2022 (Barshay, 2024; NCES, 2022). Recent studies also indicate that many college students continue to prefer online and blended learning formats, prompting institutions to expand their virtual course offerings (Garrett et al., 2023).

However, despite this growth, research has found that dropout rates and satisfaction levels in STEM-related online courses are significantly lower compared with non-STEM courses (Newsome et al., 2022; Owston et al., 2020). Several factors contribute to this disparity. STEM online courses often rely heavily on lecture-based instruction and lack student-centered learning approaches, making it difficult to replicate hands-on activities like laboratory experiments (Hou et al., 2024; McIntyre et al., 2025). Furthermore, online learning environments place greater responsibility on students to manage their own learning while offering fewer opportunities for interpersonal interaction—both of which are critical for sustaining motivation (Smith Jaggars & Xu, 2016). These challenges can be particularly acute for students from groups historically marginalized in STEM and higher education, many of whom attend broad-access institutions (Beasley & Fischer, 2012; Hillman, 2022).

In this context, self-directed learning (SDL), which includes students' motivation, metacognitive processes, and applied learning strategies, emerges as a crucial factor for success in online STEM courses (Yarnall et al., 2023). Accordingly, recent efforts have aimed to embed supports that cultivate SDL skills and reduce attrition (Yu et al., 2024). For example, online interventions have incorporated structured reflection activities, instructional resources that introduce and model SDL strategies, and collaborative learning opportunities that promote peer interaction and shared learning. These three strategies have shown promise in enhancing students' SDL (Burkander et al., 2024). However, most existing studies examine individual SDL constructs in isolation, such as academic self-efficacy or metacognition (Broadbent & Poon, 2015), rather than capturing how multiple SDL dimensions co-occur within students. Given that SDL traits are interrelated, it is essential to examine patterns or profiles of SDL using a person-centered approach (Marsh et al., 2009). This approach allows for the identification of distinct student clusters based on multiple SDL constructs, offering a more holistic view of learner variability.

Integrating this approach, our study uses a model-based clustering method to identify SDL profiles among undergraduates enrolling in STEM courses offered at broad-access institutions. We also investigate how student-level demographic and academic characteristics predict profile membership, and whether technology-based SDL interventions (the three strategies above) influence students' likelihood of shifting between profiles over time. To guide this investigation, we address the following research questions: *(1)What are the SDL profiles of undergraduate students enrolled in online STEM courses at broad-access institutions based on eight key constructs? (2) What student-level characteristics predict the likelihood of membership in each SDL profile? and (3) How does exposure to technology-based interventions affect students' likelihood of belonging to each SDL profile over time?*

Theoretical Framework

This study is grounded in a multidimensional view of SDL that emphasizes the interplay of motivational, metacognitive, and applied learning strategies (Yarnall et al., 2023). Drawing from self-regulated learning theory, traditional SDL, and self-determination theory, this framework centers the learner as an active agent in their own educational process—particularly relevant in STEM contexts where persistence and adaptability are critical. Motivationally, SDL requires a sense of agency, competence, and relatedness (Ryan & Deci, 2000), which fuel learners' persistence and goal orientation. Metacognitively, students must plan, monitor, and reflect on their learning strategies, while applied SDL involves proactively seeking resources and support—skills shown to distinguish more effective learners (Merriam, 2001). These capacities are interconnected: Metacognitive processes are shaped by motivational beliefs (e.g., self-efficacy) and in turn guide students' application of learning strategies, such as help-seeking and time management. Unlike K–12 learners, college students in online STEM courses must take greater ownership of their learning, relying less on external structures and more on self-initiated strategies.

Methods

Participants and Instruments

A total of 1,516 undergraduate students from four broad-access U.S. institutions (A, B, C and D) participated in the study. This study is part of a larger initiative to explore how technology-based instructional strategies can help students develop SDL and succeed in online STEM courses. Eligible instructors taught multiple sections of the same online or hybrid gateway STEM course and selected one section to receive the intervention, with another serving as the comparison group. Courses spanned a range of disciplines, including biology, chemistry, computer science, earth science, mathematics, and others. Of the total participants, 53% were enrolled in course sections implementing one or more of the strategies (intervention group). Demographic characteristics included 66% identifying as female, 45% as full-time students, 50% enrolled entirely online, 30% first-generation college students, and 48% receiving Pell Grants. Racial/ethnic composition was 32% White, 22% Latine, 21% Black/African American, 7% Asian, and 7% multiracial, and the remaining did not provide racial/ethnic information.

Students completed surveys before and after the intervention, assessing three key domains: motivation, metacognition, and applied learning strategies. Motivational processes included growth mindset, self-efficacy, and sense of belonging. Growth mindset was measured using Dweck et al.'s (1995) scale, and self-efficacy and belonging were drawn from the PERTS survey (Hanson, 2017). Metacognition was measured using the regulation of cognition constructs (i.e., comprehension monitoring, debugging, and evaluation) from the Metacognitive Awareness Inventory (Schraw & Dennison, 1994). We treated these constructs as one factor, following suggestions from previous work (Alotaibi, 2024; Rachmatullah et al., 2026). Applied learning strategies included help-seeking, time management, and learning strategies. Help-seeking and time management were assessed using the Online Self-Regulated Learning Questionnaire (OSLQ; Barnard et al., 2009), while learning strategies were measured using the Learning Strategies Inventory (McGuire et al., 2015).

Intervention

To develop relevant and scalable instructional supports, we first presented a set of candidate strategies—identified through a literature review—to STEM instructors and gathered their input and interest. Based on their feedback, we finalized a set of three strategies and invited instructors to participate in co-designing these strategies for implementation in online courses. A key design principle was ensuring that each strategy could be easily embedded into any learning management system (LMS) using commonly available tools.

Strategy 1: Prompts

Short-answer reflection prompts focused on goal-setting, task-planning, and weekly content reflection (e.g., *What assignments do you need to complete this week? Which concepts do you feel you mastered?*). Instructors received four sets of prompts and a suggested implementation timeline. Guidance was provided for LMS integration (e.g., using the quiz feature), and instructors were encouraged to adapt the prompts to their course context.

Strategy 2: Videos

Three videos (7–10 minutes each) were developed, covering specific SDL skills or mindsets. Each video included an overview of the skill, two to three practical strategies for improvement, links to additional resources, and a reflection activity. Students were encouraged to self-assess their current abilities and select strategies for growth. Instructors could embed the videos into their course LMS, with flexibility to require or recommend them.

Strategy 3: Student-Peer Interaction and Networking (SPIN)

SPIN consisted of three components: (1) an introductory survey to identify shared nonacademic interests (e.g., hobbies, work responsibilities); (2) a group activity facilitated by the instructor based on those shared interests; and (3) discussion opportunities via the LMS or another platform, during which students shared concepts they understood or struggled with, along with helpful resources.

Data Analysis

To address RQ1, we used item response theory (IRT) to revalidate our instruments and generate standardized *theta* scores for each of the eight SDL constructs. These scores were used in the model-based clustering analysis using the *mclust* package in R. The optimal model was selected based on the lowest Bayesian Information Criterion (BIC), and cluster (or profile; terms used interchangeably throughout) characteristics were described using mean construct scores. We also extracted posterior probabilities indicating each student's likelihood of belonging to each cluster.

For RQ2 and RQ3, we ran multilevel models with a repeated measures structure (Time at Level 1, Student at Level 2). The dependent variables were students' posterior probabilities for each cluster, with separate models estimated per cluster. Model 1 (RQ2) tested which student-level predictors influenced cluster membership. Model 2 (RQ3) included a Time × Intervention interaction to assess changes in cluster membership likelihood as the impact of the intervention.

Findings

Identification and Characterization of SDL Clusters

Model-based clustering identified the EVE model (ellipsoidal, equal volume and orientation) with three clusters as the best fit for the data (log-likelihood = −19,455.52; BIC = −39,496.19). Figure 1 displays the defining characteristics of each cluster. **Cluster 1** appears to represent the most adaptive and self-regulated learners. These students report high self-efficacy and apply concrete strategies for managing their time and learning. Their strong metacognitive awareness suggests they regularly monitor and reflect on their progress, positioning them well for success in autonomous learning environments.

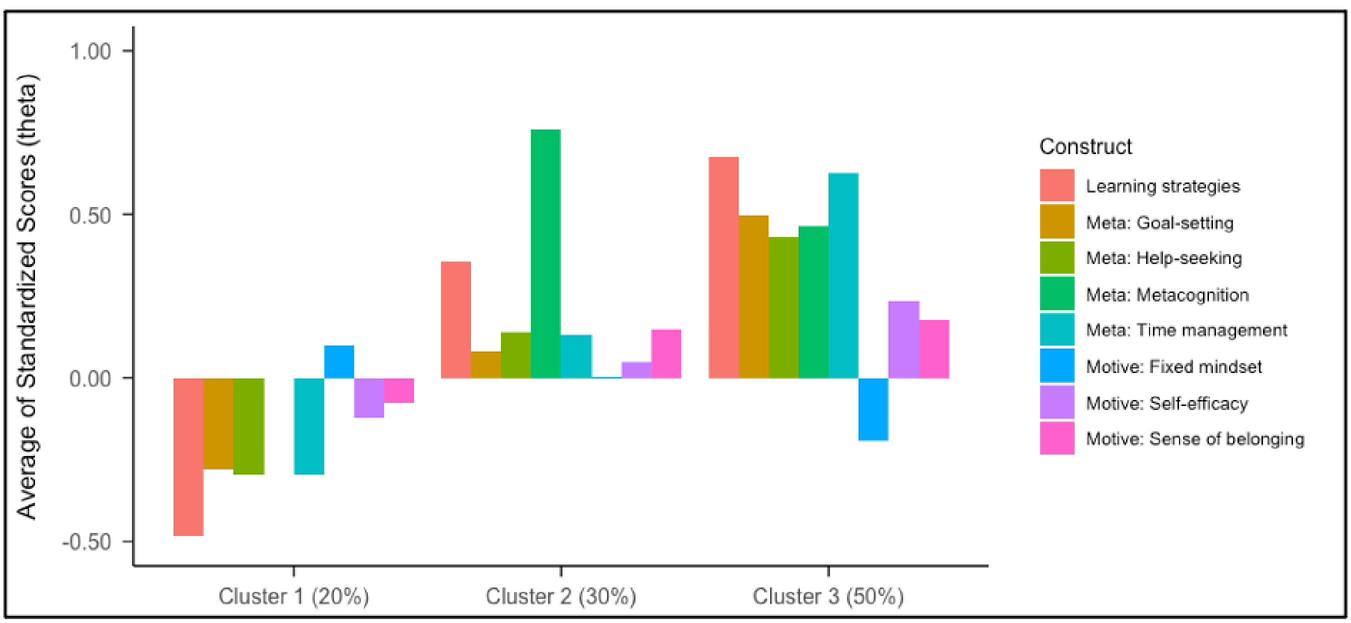
Cluster 3, by contrast, represents students who may be most at risk. They display a high fixed mindset, low self-confidence, and limited use of applied learning strategies. This group may experience disengagement, anxiety, or uncertainty about how to succeed in independent learning settings.

Their profile highlights the need for targeted interventions and supportive learning environments promoting growth mindset and belonging. **Cluster 2** presents a more nuanced profile. These students demonstrate strong metacognitive skills—they plan, monitor, and adjust their learning strategies—but may lack confidence (self-efficacy) and sense of belonging. While they are reflective and strategically aware, their insights may not always translate into action or sustained motivation. This group could benefit from supports that strengthen self-efficacy and social-emotional engagement to help convert awareness into momentum.

Predictors of Cluster Membership and Effects of Intervention

Table 1 presents the results of the multilevel models predicting cluster membership and the effects of the intervention. For **Cluster 1**, Black/African American students had a significantly higher probability of belonging to this high-SDL group compared with White students. Additionally, students enrolled in mostly face-to-face courses with an online component were more likely to be in Cluster 1. However, this result should be interpreted with caution because of the small number of students in these settings. For **Cluster 2**, Pell grant recipient status was associated with a higher probability of membership, suggesting that students from lower-income backgrounds were more likely to fall into this reflective but less confident group. Year of birth was also a positive predictor indicating that younger students were more likely to belong to this cluster. For **Cluster 3**, Black/African American students were significantly less likely to belong to this lower-SDL profile compared with White students. Part-time enrollment and enrollment at Institution C were also negative predictors of membership in this group. Similar to Cluster 2, year of birth was positively associated, suggesting younger students were more likely to fall into this at-risk cluster.

Figure 1. Characteristic of each identified SDL cluster based on the eight constructs.



We examined how students' probabilities of belonging to each SDL cluster changed from pre- to post-test and whether these changes were influenced by the intervention. For **Cluster 1**, post-test time significantly predicted a small increase in membership probability, regardless of condition, suggesting that students generally became more likely to belong to this high-SDL cluster over time. Importantly, the Time × Intervention interaction was also significant, indicating that students in the intervention group experienced a greater increase in Cluster 1 probability than those in the comparison group.

For **Cluster 2**, neither time nor the interaction effect was significant, indicating that membership probabilities remained stable across time and conditions. Lastly, for **Cluster 3**, we found a significant decrease in post-test membership probability, suggesting that students overall became less likely to belong to this low-SDL cluster. However, the Time × Intervention interaction was not significant, indicating that the reduction was not specifically attributable to the intervention. In summary, the intervention had a positive, time-sensitive effect on increasing the likelihood of students joining Cluster 1. Cluster 3 membership declined over time for all students, while Cluster 2 remained unchanged across both time and treatment conditions.

Contribution to STEM Teaching and Learning

Our findings add to the growing literature on SDL in online STEM education and offer practical implications for instructors and support staff. SDL profiles can help faculty and advisors tailor instruction and support. For instance, students in Cluster 2, who are reflective but not yet action-oriented, may benefit from scaffolds that boost confidence and strategic follow-through, while those in Cluster 3, who struggle with engagement and self-regulation, may need more intensive support. The findings also emphasize the importance of equity-conscious interventions that address varied SDL capacities and enable early, targeted outreach to at-risk students. Importantly, the intervention was associated with a shift in students' SDL profiles: Regardless of the cluster students belong to at the start of the course, those exposed to the SDL supports were significantly more likely to transition into Cluster 1, the profile characterized by the strongest SDL skills. This pattern suggests that technology-based strategies can strengthen key SDL skills like self-efficacy, time management, and metacognition, supporting student success in autonomous, digital STEM learning environments.

Table 1. Significant Predictors of Posterior Probability of SDL Cluster Membership and Intervention Impact

Variable		Cluster 1				Cluster 2				Cluster 3			
		Model 1		Model 2		Model 1		Model 2		Model 1		Model 2	
		b	*p*	*b*	*p*	*b*	*p*	*b*	*p*	*b*	*p*	*b*	*p*
Intercept		4.46	.141	4.33	.152	***9.64***	***.008***	***9.70***	***.007***	-12.83	***.002***	-12.77	***.002***
Level 1: Time	Post-test	***0.06***	***.002***	0.00	.907	-0.01	.627	0.02	.568	-0.05	***.017***	-0.03	.415
Level 2: Student	Intervention Group	0.03	.108	0.00	.850	-0.04	.077	-0.03	.313	0.01	.684	0.02	.421
	Race/Ethnicity (vs. White)												
	Black/African American	***0.06***	***.033***	***0.06***	***.030***	0.04	.274	0.04	.280	-0.11	***.007***	-0.11	***.007***
	Pell Recipient	-0.03	.137	-0.03	.156	***0.09***	***.001***	***0.09***	***.001***	-0.05	.058	-0.06	.055
	Part-time Student (vs. Full Time)	0.03	.135	0.03	.114	0.04	.101	0.04	.110	-0.07	***.012***	-0.07	***.011***
	Institution (vs. Institution D)												
	Institution C	***-0.07***	***.015***	***-0.07***	***.019***	-0.01	.807	-0.01	.776	0.08	***.044***	0.08	***.047***
	Year of Birth	0.00	.150	0.00	.164	***0.00***	***.010***	***0.00***	***.009***	0.01	***.001***	0.01	***.001***
	Time × Intervention			***0.10***	***.007***			-0.05	.226			-0.05	.295
Interclass Correlation (ICC)		.340		.344		.323		.323		.474		.474	

Note. Multilevel model estimates for student-level and contextual predictors of the likelihood of belonging to each SDL cluster. This table presents only variables that significantly predicted SDL cluster membership ($p < .05$) in Model 1 (all predictors) and Model 2 (Time × Intervention). Nonsignificant predictors omitted for brevity include first-generation status, gender, cumulative GPA, credits earned, first semester student status; race/ethnicity (Asian, Latine, Multiracial, Native American, Prefer not to answer/ Unknown); Institutions A and B; and hybrid course formats with varying online/face-to-face proportions.

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The Postsecondary Teaching with Technology Collaborative (the Collaborative) is a U.S. Department of Education, Institute of Education Sciences R&D center, co-led by SRI Education and the Community College Research Center at Teachers College, Columbia University, in partnership with Achieving the Dream. The Collaborative uses research findings to build the capacity of institutions and instructors to establish inclusive learning environments and incorporate technology in ways that improve learning and success in postsecondary online courses. Our research analysis aims to contribute to knowledge and understanding of how instruction can support students to employ a constellation of motivational and metacognitive processes and certain applied learning processes—which we refer to as self-directed learning (SDL)—to manage their learning more effectively in online courses and increase their postsecondary success.

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