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Coping with the transition to remote instruction: Patterns of self-regulated engagement in a large post-secondary biology course

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ABSTRACT

The COVID-19 disruption presented considerable challenges for university students, requiring the sudden need for increased engagement in remote learning environments and the ability to cope with academic and familial demands. To examine how students self-regulated their learning during the disruption, we surveyed undergraduates (n = 226) enrolled in four sections of a large biology course once during the first week of the semester, immediately after the disruption, and through the end of the semester. The results indicated significant decreases in student motivation, increases in students' perceived costs, and quadratic changes in self-reported coping strategies and mental depletion during disrupted learning. In a final model, students' self-efficacy and perceptions of cost, as well as feelings of anger and personal responsibility for family combined to form a parsimonious set of predictors that explained variance in course performance.

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The COVID-19 disruption required a rapid transition to emergency remote instruction for students enrolled in university courses (Hodges et al., 2020). After years of reluctance on behalf of universities to adopt cohesive approaches to digital learning and online instruction (Bacow et al., 2012), reports of confused instructors, flailing administrators, and—most notably—frustrated students were widespread. Students were forced to vacate the normalcy of their in-person educational experiences and relocate home (or to some other off-campus location) to shelter during the pandemic. The transition was accompanied by a wide range of extremely difficult challenges for students, including loss of employment and personal income for themselves and their families, deep uncertainties about the future of their academic endeavors, and, of course, the dangers of the virus itself.

Yet, students were still expected to perform in school. When faced with challenging academic tasks students must sustain their motivation and self-regulate their emotions and cognitions in order to successfully engage and learn (Schunk & Greene, 2018). The disruption presented considerable challenges for university students, requiring the sudden need for increased engagement in computer-based learning environments and the ability to cope with external demands related to this pandemic. Because the contextual features of learning environments (e.g., differences between classroom and virtual settings) and learner characteristics (e.g. motivation, affect, prior knowledge) combine to shape the strategies students use to learn (Winters et al., 2008; Xie et al., 2019), the disruption required students to adapt to the changing circumstances in order to succeed academically.

The ability to successfully navigate changing academic circumstances is underscored by students' ability to strategically regulate the redefinition of academic tasks due to changes in their learning

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environments. When the definition of an academic task shifts, students are required to update their perceptions of the task, including the reasons for performing the task, their emotional response to the shift, and the strategies they use to complete the task. The task redefinition process may also impose additional demands, creating a set of circumstances where the costs of achieving one's learning goals become greater than the values. When the pandemic forced students and instructors to remote instruction, we expanded an existing study to examine potential shifts in student self-regulated learning and motivation by administering weekly check-in surveys. The surveys were administered to students enrolled in a gateway life science course each week after the transition to remote instruction. We analyzed the data using a combination of quantitative and text mining approaches to examine shifts in their patterns of motivations, self-regulation, and engagement.

Implications of disruption on self-regulation and learning

The transition to remote instruction created a profound disruption to student learning, which increased the demand for self-regulation and adjusted strategy use. For example, instead of engaging in classroom activities, sharing notes and information with study partners, and working with tangible learning materials (e.g., in the laboratory), students were required to learn new information from online videos, engage with other students in digital chats, and visualize otherwise physical processes using diagrams or animated videos. Shifting patterns of engagement and strategy use to adapt to remote instruction requires control over learning behaviors (Schunk & Greene, 2018). Self-control is a finite resource that, when depleted, can lead to decreases in motivation, self-regulation, and academic performance (Hagger et al., 2010). Depletion often occurs when clashing demands require people to make sacrifices to reach long-term goals (Baumeister & Vohs, 2007). Under these kinds of circumstances, students move from strategically pursuing learning goals to coping with outside demands (Boekaerts, 1996b).

The COVID-19 disruption required students to adjust to a new learning context, creating tensions between academic and familial demands, and likely depleting capacity to regulate their learning. To successfully navigate disrupted academic tasks, students needed to manage their academic content while coping with other personal events. Students who maintain high expectancy and value for success (Eccles & Wigfield, 2020), adaptive achievement goals (Elliot & Hulleman, 2017), and evidence of behavioral engagement and self-regulated learning (Bernacki, 2018) are likely to exhibit high levels of academic achievement. Maintaining patterns of engagement indicative of motivated, self-regulated learning should be related to less need (or greater ability) to cope with outside stressors and be related to stronger academic performance during tense periods such as the COVID-19 disruption.

Theoretical framework of self-regulated learning and motivation

Self-regulation is an integrated metacognitive process informed by motivational and affective responses to environmental demands (Ben-Eliyahu & Linnenbrink-Garcia, 2015; Greene, 2018). In the self-regulated learning (SRL) process, students plan for learning, execute and monitor the use of learning strategies, and reflect upon their success and failures as they adapt and continue to pursue learning goals. The SRL process can be facilitated or undermined by students' motivations and affective experiences (Ben-Eliyahu & Linnenbrink-Garcia, 2015). Endogenous factors such as goal setting, self-evaluative judgements have long been considered critical to voluntary action management (Karoly, 1993) and factors such as motivation, affect, and metacognition have been posited to have distinct influences on the regulation of learning behavior in a wide variety of contexts (Efklides, 2017). Many SRL theoretical models posit relations among motivation, affect, engagement, and regulatory processes. For example, iSRL (Ben-Eliyahu & Linnenbrink-Garcia, 2015) and the MARSL (Efklides et al., 2011) have become popular models for investigating how individuals' affective responses to task contexts and processes influence

their learning and achievement. In these models, task- and person-level variables interact and proceed dynamically where individuals respond to initial task conditions, and changes in those task conditions further influence students' self-regulatory processes. A key set of person-level variables that influence this complex process is the set of motivations, perceptions, and beliefs that a learner brings to a task, and the way that these evolve during task engagement and exert influence on students' engagement during learning.

Students with greater expectancy for success and perceived value (i.e., Eccles & Wigfield, 2020) for academic learning are more likely to engage more deeply during learning, exhibiting higher levels of planfulness and metacognitive monitoring. Students who experience positive, activating emotions are also more likely to self-regulate in adaptive and effective ways (Pekrun et al., 2007). Changes in these processes, for good or for bad, are triggered by the reciprocal interaction between the person and their environment (Bandura & McClelland, 1977; Efklides, 2011) and can require learners to *re*-define the task based on their experiences so they can adapt to changes in the affordances provided or constraints imposed by a task, their updated perceptions, motivations and goals, and beliefs so they can productively engage in learning. The onset of a global pandemic is was novel occurrence that is clearly disruptive to many aspects of life, including learning. No literature exists to inform the study of ways learning is disrupted, but theories of self-regulation and self-regulated learning provide useful lenses for considering the process of task redefinition, including both changes in the in-task demands imposed directly on learning processes, as well as on the other responsibilities one must simultaneously manage while learning, and which might deplete one's resources available to do so (i.e., family demands). This might force a shift of focus from pursuit of learning goals to a focus on coping, and concomitant aim to cope in order to continue learning (Boekaerts, 1996b, Boekaerts & Niemivirta, 2000).

In the following sections we consider the ways that students' self-regulatory processes may be engaged by an interruption after initiation of a learning task, the ways this shift in the task context—and the broader environmental context in which they are situated—may alter students' perceptions of its value and cost (Wigfield & Eccles, 2020), and the ways that task engagement may influence student feelings of efficacy and depletion. We first explore self-regulated learning and expectancy value theories of motivation as they influence the decision to initiate and sustain task engagement, then consider such engagement through self-regulated learning theory, and in particular, models that focus on learners' capacity to pursue their goals or temporarily cope with obstacles that prevent such pursuit.

Expectancy-value theory

Individuals' tendency to engage in the learning process is informed by their motivations, including their expectancy that they can productively engage in a task in a way that will enable them to attain a goal that they value, and that warrant the costs of engagement (Eccles et al., 1983). Those costs may include effort they must expend, opportunities they must forgo, and psychological costs they must endure in order to advance through the task en route to obtaining the perceived value it can confer. For example, student may perceive the stress and sacrifice associated with learning is not worth the effort (Flake et al., 2015). When students are enrolled in a course where the costs outweigh the values in their motivation to perform, task engagement requires a more elaborate variety of self-regulated learning which involves both learning and coping (Boekaerts & Niemivirta, 2000). Students may be required to adjust their motivations and strategy use to cope with external demands and costs.

Implications of disruption for task values

In a recent reconceptualization of Expectancy Value theory, Eccles and Wigfield (2020) underscore the ways which students defines their experience of task value. This situated perspective

(Lave & Wenger, 1991) is well equipped to describe the task redefinition process (Winne & Hadwin, 1998) as students refine their understanding and adjust their perceptions over the semester to engage accordingly. It can be further leveraged to understand the changes in student experiences due to growing task understanding and progress shifts according to the features of the task caused by disruptions. We thus examine in this paper, students' initial perceptions of task value, the initial shift in those perceptions after the pivot to online instruction, and additional changes in task value thereafter, as students continued to mature in their understanding of a constantly changing task environment. This initial and evolving set of perceptions is an essential driver of students' self-regulated learning during complex tasks (Schunk & Greene, 2018).

Self-regulated learning

Students who self-regulate their learning engage in the process of appraising the context of the learning task, as defined by the affordances provided and the constraints imposed on the learner (Winne & Hadwin, 1998). The parameters of these affordances influence how students set learning goals and develop plans for achieving those goals, enact plans, and meta-cognitively monitor progress toward their learning goal. In the achievement goal literature, these goals are often defined according to mastery and performance dimensions, where students may pursue goals related to learning material and do well on assessments or avoid having to demonstrate their knowledge because they are not confident in their abilities (Elliot & Murayama, 2008). Parallel to the goal setting process is monitoring whether their chosen tactics are advancing them toward their goal, or whether they should alter their approach, their goal, or their choice to engage in learning. Students self-regulate in an ongoing fashion, where an initial goal, plan, and set of strategies can be adapted in future learning cycles, dependent on the experiences that precede it. Students' initial decision to engage in a task is driven by their belief that they possess the ability to successful engage in a task, and that it conveys sufficient value that they should undertake it (Zimmerman, 2000). Thereafter, such perceptions of the values and costs must be sustained, or else a student is likely to abandon the task (Schunk & Greene, 2018).

Coping and task redefinition during academic challenge

Whereas some models of self-regulation focus primarily on the cognitive and metacognitive processes involved in learning, other models broaden consideration of the learning experiences to accommodate instances where motivational and emotional aspects of learning tasks are sufficiently challenging to the individual that a learning goal must be periodically set aside while the individual shifts to a focus on coping through the task (Boekaerts, 1996a, 1996b; Boekaerts & Niemivirta, 2000). Under these circumstances, students most redirect their energized action toward managing costs associated with the learning experience, as opposed to strategically attaining their desired learning goal. In this study we examine whether students acknowledge this shift when describing their self-regulation of learning during weeks of disruption when the nature of their learning task changed—and may have continued to change as they tried to learn.

Task definition and redefinition

Learners who initially engage in a learning task will have done so under the context assumptions and environmental assumptions originally made when they defined the task as initially observed (Winne & Hadwin, 1998). Thereafter, learners are periodically expected to update their perceptions of the task based on the progress they have made through it, and a growing understanding

of how the task affordances may benefit them, and how the constraints limit what can be gained or focus their task engagement. These assumptions refer to a task that is itself static (i.e., resource and constraints are fixed for the duration), and it is the learners' evolving experience that informs their redefinition. During the spring semester of 2020 when the COVID-19 pandemic reached the United States, the task was *not* static; students enrolled in university courses experienced a disruption to the learning task that required a *re*definition of what that they had initially appraised at the outset of the semester.

The disruption necessitated "quick pivot" (Gardner, 2020) of the learning task when the learning environment shifted from a face-to-face setting to an often hastily developed format involving some combination of synchronous and asynchronous learning activities in place of the activities they had undertaken through the first weeks of the course. This pivot thus required an initial task re-definition, and additional task redefinitions often were required thereafter as learners became familiar with new tools and their affordances and constraints. Students also needed to come to understand new challenges imposed by the instructors' assessments, rapid changes to their living and study conditions, and other factors such as access to technology that continued to impact their learning throughout the semester. These ongoing redefinitions can impact the way the students perceive a task, and can also stress the self-regulatory capacities students have to sustain their engagement.

Study rationale and research questions

The purpose of the present study was to evaluate the effects of the COVID-19 disruption on students enrolled in a large, gateway, face-to-face introductory biology course that many students take multiple times en route to earning their degree. At mid-semester, students were forced to move from a face-to-face classroom setting to engaging in a fully remote format hosted on a learning management system (LMS) course site. We examined how the disruption influenced students' motivation to learn, management of course content, ability to cope with personal and academic events, feelings of mental depletion and, in turn, how these factors predicted overall achievement in the course. Our research questions were as follows:

- Research Question (RQ)1: Do students' motivations to learn at the beginning of the semester (Time 1) shift immediately following the disruption to learning (i.e., online transition; Time 2)?
- RQ2: Did the disruption to instruction influence students' feelings (1) about their ability to cope with personal and academic events, or (2) of mental depletion during the weeks spent social distancing and adapting to remote instruction?
- RQ3: Do students' motivation to learn, ability to cope with personal and academic events, feelings of mental depletion, and within-course behaviors predict their overall academic achievement in the course?

Methods

Participants

Undergraduate students (n = 226) enrolled in four sections of a biology course participated. The population enrolled in the course was 0.1% American Indian, 28.0% Asian, 5.4% African American, 30.9% Hispanic, 0.7% Pacific Islander, 1.0% nonresident; 10.3% two or more races, 0.2% unknown, 23.5% White, and 63.8% female. The course included topics in cellular and molecular biology. Twenty-five percent of students drop out, fail, withdraw, or earn grades requiring reenrollment to satisfy their degree requirements, and the course has never been taught fully online before the transition to remote instruction.

Measures

Motivation to learn questionnaire

The 44-item Motivation to Learn Questionnaire included five scales measuring students' Achievement Goals, Self-Efficacy for STEM courses, and their perceptions of values and costs. Table 1 presents the Cronbach's internal consistency reliability coefficients, means, and standard deviations for each time point across each scale.

Achievement goal questionnaire. Achievement goals were measured by nine items that provided scores on three goal subscales, Mastery Approach, Performance Approach, and Performance Avoidance. The items were drawn from Elliot and Murayama's Achievement Goal Questionnaire-Revised (2008); mastery avoidance goals were not assessed given the introductory nature of the content, and the limited opportunity for students to indicate a goal of retaining such knowledge. The items were measured on a seven-point Likert-type scale from *strongly disagree* to *strongly agree.* Mastery Approach assessed students' desire to learn or master material in their STEM course (three items; sample item: "My aim is to completely master the material presented in this course"). Performance Approach assessed students' desire to outperform others (three items; sample item: "My goal is to perform better than the other students"), whereas Performance Avoidance assessed students' desire to avoid showing incompetence (three items; sample item: "My goal is to avoid performing poorly compared to others.").

Self-Efficacy. The Self-Efficacy scale measured students' beliefs about their ability to be successful in their current STEM course across five items drawn from the Patterns of Adaptive Learning Scale (Midgley et al., 2000). The items were measured on a six-point Likert-type scale from *strongly disagree* to *strongly agree* (sample item: "I'm certain I can master the skills taught in this course").

Perceptions of task value. Scales assessing student's task value perceptions included 12 items measured across three subscales, Attainment Value, Intrinsic Value, and Utility Value. The items were adapted from Eccles and Wigfield (1995) by Perez et al. (2014). Attainment Value assessed the importance of STEM to students on two six-point Likert-types scales from *not at all worthwhile* to *very worthwhile* and *not at all important to very important* (four items; sample item: "Is the amount of effort it will take to do well in your STEM courses worthwhile to you?"). Intrinsic Value assessed students' feelings of enjoyment and interest in STEM courses on three six-point Likert-type scales from v*ery boring* to *strongly interesting, I dislike them very much* to *I like them very much*, and *strongly disagree* to *strongly agree* (four items; sample item: "The concepts and principles taught in this course are interesting."). Utility Value measured the degree to which students found STEM useful for their daily lives and future career on two six-point Likert-type scales from *not at all useful* to *very useful* and *strongly disagree* to *strongly agree* (four items*;* sample item: "Being good at science will be important when I get a job.").

Costs. The Costs scale included 12 items measured across three subscales, Effort Cost, Opportunity Cost, and Psychological Cost. The items were adapted from Perez et al. (2014) and were measured on a six-point Likert-type scale from *strongly disagree* to *strongly agree*. Effort Cost assessed students' perceptions about the effort required to be successful in their STEM courses (four items; sample item: "Considering what I want to do with my life, taking STEM courses is just not worth the effort."). Opportunity Cost assessed students' perceptions of the loss of valued personal relationships while pursuing their current STEM course (four items; sample item: "I worry about losing track of some valuable friendships if I'm spending a lot of time on this course and my friends are not."). Psychological Cost assessed concerns about how failure in their current STEM course would have an adverse effect on their emotional state (four items; sample item: "My self-esteem would suffer if I tried in this course and was unsuccessful.").

Table 1. Motivation to learn questionnaire reliability coefficients, means, and standard deviations.

		Time 1		Time 2		Time 3	
Scale	Items	α	*M(SD)*	α	*M(SD)*	α	*M(SD)*
Achievement goals							
Mastery approach	3	0.932	6.39 (1.05)	0.899	6.27 (0.89)	0.925	5.93 (0.95)
Performance approach	3	0.811	5.96 (1.06)	0.828	5.76 (1.02)	0.917	5.63 (1.09)
Performance avoidance	3	0.822	5.88 (1.19)	0.892	5.75 (1.22)	0.927	5.65 (1.20)
Self-efficacy	5	0.894	5.09 (0.74)	0.919	4.84 (0.77)	0.945	4.72 (0.78)
Value beliefs							
Attainment	4	0.693	5.35 (0.49)	0.808	5.13 (0.66)	0.819	5.04 (0.63)
Intrinsic	4	0.906	5.23 (0.77)	0.892	4.94 (0.96)	0.937	4.82 (1.10)
Utility	4	0.924	5.41 (1.02)	0.899	5.12 (1.13)	0.911	4.93 (1.11)
Cost							
Effort	4	0.910	2.59 (1.49)	0.916	2.88 (1.55)	0.910	3.08 (1.47)
Opportunity	4	0.941	2.42 (1.52)	0.955	2.61 (1.57)	0.968	2.82 (1.63)
Psychological	4	0.838	4.40 (1.48)	0.853	4.61 (1.47)	0.861	4.60 (1.47)

Note. n = 226.

Weekly check-in tasks

During the five weeks immediately following the shift to remote instruction, students completed Weekly Check-In Tasks in lieu of planned assignments intended to indicate face-to-face attendance. Weekly Check-In Tasks required students to respond to prompts to indicate their ability to cope and manage learning, and to report the degree of depletion they felt during that semester week. As is typical of dense data collection schedules (e.g., experience sampling) and broad-spanning surveys designed to assess multiple aspects of a respondent's experience, we relied on single item indicators. We followed the guidance of those who develop and validate such measures (Fisher et al., 2016; Petrescu, 2013): items should be sampled from existing scales, and when none exist, single item indicators can be effective when they sample simple, easy-to-understand and concrete constructs.

As existing scales focus on processes like time management and organization under typical learning conditions (e.g., time management, organization scales of the Motivated Strategies for Learning Questionnaire, Pintrich et al., 1993) and there were not existing scales that assessed the specific processes we intended to investigate, we designed single item indicators. When the phenomenon we wished to investigate was generally well-understood, we explicitly stated the variable we intended to assess within the text of the item (i.e., managing and coping). When the term was a less commonly used one, we operationally defined that less familiar term within the item we posed to respondents (e.g., depletion).

Coping was measured with a prompt asking how well students were able to cope with current personal and academic events in their life that they experienced that week (i.e., in response to a single item "Overall, how are you coping with personal and academic events in your life this past week?" Students responded using a five-point Likert-type scale from *very well* to *very poorly*. Students reported their *Managing* of learning by responding to a prompt to report "How well are you managing your learning in this course this past week?" using a five-point Likert-type scale from *very well* to *very poorly*. Students reported feelings of *Depletion* in response to a single item "How depleted—mentally overwhelmed, tired, exhausted, or emptied out—do you feel by all you had to do to manage your learning this past week?" using a five point scale that ranged from *very depleted* to *not at all depleted*.

The first and final of the Weekly Check-In Tasks also included items about the transition to online learning following the COVID-19 disruption. Specifically, students were asked the following open-ended questions: (1) "In a few sentences, please elaborate on the ways the COVID-19 disruption has affected your approach to this course;" (2) "In a few sentences, describe how you intend to change your study strategies during the transition to a fully online course;" (3) "In a few sentences, describe how and when you studied course materials in Canvas [the course LMS site] to prepare for exams." Analysis of the open-ended items helped to bolster our conclusions about student experiences in the absence of a control or comparison group.

Academic achievement

Final course grades were used to operationalize academic achievement. The final course grades were composed by performances on five examinations, pre- and post-lecture assignments, and quizzes administered in the learning management system (LMS). Final grades were measured on a continuous scale from 0% to 100%.

Procedures

During the first week of the course (referred to as Time 1), students completed a consent form and the Motivation to Learn Questionnaire (MLQ). After the COVID-19 disruption, students were immediately transitioned to online instruction for the remaining weeks of the semester. Using spring break as a buffer, instructors prepared online instructional materials and loaded them to the LMS site. The MLQ was then re-administered directly after the transition to online instruction (referred to as Time 2) and during the last week of the semester (referred to as Time 3) in order to gauge changes in students' motivation to learn as the design of the course shifted. We examined these three time points accordingly. As an additional component of the data collection, the instructors implemented a weekly check-in activity that contained survey items and open-ended response questions that addressed various facets of self-regulated learning and depletion (i.e., ability to cope, ability to manage, and feelings of depletion). In partnership with our research team, these items were administered during the final weeks of online instruction (i.e., Weeks 10 through 15). Instructors assigned this "check-in" activity and monitored students' self-reported capacity for coping, managing, and their experiences of mental depletion via the single Likert-scaled items and open response fields. Students responded to open-ended questions during week 10 and 15, and the coping, managing, and depletion items every week following the disruption (at 6 time points). Student academic performances, including final course grade, was extracted from LMS course gradebooks. Figure 1 presents the timeline of events across the semester.

Analysis

All Likert scale data taken from the MLQ, coping, managing, and depletion items were cleaned and coded using IBM SPSS 26. Preliminary analyses included examinations of missing data and assumptions checking. To handle missing data, we utilized a nonparametric missing value imputation using a random forest algorithm to impute missing values (Stekhoven & Bühlmann, 2012). This approach is particularly useful for mixed-type data and handling complex interactions and nonlinear relations. The approach also yields an imputation error estimate that can be used to assess accuracy of imputation iterations. Analysis of missing data patterns indicated that missing data were relatively evenly spread across the variables. Variables were missing between 23 and 63 responses. The largest amount of missing data occurred for the week 12 coping question, indicating that variables were not more likely to be missing in the final weeks of the semester. Inspection of means, standard deviations, and bivariate correlations indicated the student responses to the items were interpretable. Estimates of means and standard deviations for listwise and pairwise deletion on the data set were relatively similar, providing evidence to rule out the possibility of

Figure 1. Timeline of events across the semester.

data missing not at random. We proceeded with five imputations using the random forest algorithm, choosing the iteration with the lowest error estimate. Assumptions checking proceeded with the examination of descriptive statistics, including means and standard deviations, for evidence of normality. Measures were spaced one week apart to meet the independence assumption. The Greenhouse-Geisser correction was used because data violated the sphericity assumption.

To analyze change over time in the MLQ data, a repeated measures analysis of variance (ANOVA) with a Greenhouse-Geisser correction was conducted across the three time points for all of the motivation constructs to determine if the mean differed statistically significantly between time points. Post-hoc tests using the Least Significant Difference (LSD) procedure correction (to control for type I error) were conducted to determine if the COVID-19 disruption elicited a reduction or increase in motivation from the beginning of the semester to the week after the transition to remote learning, and then again to the end of semester (i.e., Times 1 to 3). To analyze change over time in the measures of coping, management, and depletion, a repeated measures analysis of variance (ANOVA) with a Greenhouse-Geisser correction was conducted across the six time points (i.e., weeks 10 – 15) for all the items to determine if the mean differed statistically significantly between time points. Polynomial within-subjects contrasts were examined to determine the linear shape of change. Post-hoc tests were conducted to determine if the COVID-19 disruption elicited a reduction or increase in coping, managing, and depletion from the week after the transition to remote learning to the end of semester.

To analyze the open-ended data response data, a Linguistic Inquiry and Word Count (LIWC; Pennebaker et al., 2015) text mining approach was used to convert text responses into word percentage counts associated with linguistic dictionaries. This approach to text mining leverages previously validated dictionaries to develop individual-level word count variables. LIWC software was used to analyze student opened ended responses stored in a spreadsheet. The software analyzes each row of data and counts words that are associated with the preloaded dictionary. The software assigns a word count numerical variable for the preloaded dictionaries based on each opened ended response. For example, the words associated with the "anger" dictionary, or the "family" dictionary, in each students' open-ended responses are converted to frequency counts for participants. That is, when a student writes, "I am frustrated that I have to work at home now because my little sister keeps pestering me while I am studying," words such as "frustrated" and "pestering" would be tallied under an "anger" count variable created by the software, and words such as "home" and "sister" would be tallied in the "family" word count variable created by the software. These word counts were treated as evidence for the contents of student thinking the effects of the pandemic.

To determine the best predictor of final course grade, the motivation, coping, management, depletion, and word count variables were included in a backward selection regression model to predict course performance. The backward selection method begins by entering all desired terms into the model. At each step, the least significant term is removed from the model until all of the remaining stepwise terms have a statistically significant contribution to the model. Removal probability, or the likelihood-ratio statistic for variable removal, was set to .05.

Results

RQ1: shifts in motivation

Repeated measures ANOVAs were conducted for the motivation and self-regulation study variables. A repeated measures ANOVA with a Greenhouse-Geisser correction determined that mean scores for the motivation achievement goals, self-efficacy, and perceptions of task value significantly decreased and students' perceptions of costs significantly increased. Post-hoc tests using the Bonferroni correction revealed that the COVID-19 disruption elicited significant reductions (or increases in the case of perceived costs) from the beginning of the semester to the week after the transition to remote learning for all variables except for performance avoid goals. By the end of semester, many of the study variables showed further significant increases or decreases. Table 2 provides a summary of the results, including patterns of significance across the follow

Table 2. Summary of repeated measures ANOVA findings for all study variables.

	F	*p*	η^2	MD12	MD13	MD23	Follow-up Sig
Mastery approach	$F(1.783, 14.366) = 19.974$	$p < .001$	.08	.12	.45	.34	1,3; 2,3
Performance approach	$F(1.835, 12.811) = 9.133$	$p < .001$	.04	.20	.33	.13	1,2; 1,3, 2,3
Performance avoid	$F(1.816, 6.092) = 3.487$	$p = .036$	.02	.12	.23	.11	1,3
Self-efficacy	$F(1.928, 8.746) = 24.443$	$p < .001$	.10	.25	.38	.13	1,2; 1,3, 2,3
Attainment value	$F(1.977, 5.840) = 29.852$	$p < .001$	.12	.23	.31	.08	1,2; 1,3, 2,3
Intrinsic value	$F(1.924, 10.545) = 28.037$	$p < .001$	.11	.28	.43	.13	1,2; 1,3, 2,3
Utility value	$F(1.816, 14.847) = 28.900$	$p < .001$	.11	.29	.48	.19	1,2; 1,3, 2,3
Effort cost	$F(1.954, 14.139) = 14.154$	$p < .001$	.06	−.30	−.49	−.20	1,2; 1,3, 2,3
Opportunity cost	$F(1.892, 9.910) = 7.397$	$p < .001$	.03	−.20	−.40	−.21	1,2; 1,3, 2,3
Psychological cost	$F(1.979, 3.284) = 3.073$	$p < .001$	.01	−.21	−.20	.01	1,2; 1,3

Note. TOC = Type of Change. Significance is reported at p < .05 for all omnibus tests. The follow up significance column reports significant differences between time points. Motivation time points: 1 = first week of the semester; 2 = immediately following move to online learning; 3 = last week of semester.

up tests and mean differences between time points for each measurement. Figure 2 summarizes mean ratings to Motivation for Learning Questionnaire scales by time.

RQ2: shifts in coping, managing, and feelings of depletion

A repeated measures ANOVA with a Greenhouse-Geisser correction determined that mean managing differed statistically significantly between time points, $F(4.384, 1.654) = 2.893$, $p = .018$, $\eta^2 = .01$. Examination of within subject contrasts indicated that a linear shape of change most adequately characterized the data $F(1, 1.860) = 3.378$, $p = .031$, $\eta^2 = .02$. Post-hoc tests using the LSD correction revealed that the COVID-19 disruption elicited an increase in perceptions of how well students reported managing learning from week 10 of the semester to week 14 (2.983 ± .06 vs. 3.201 ± .06, respectively), which was statistically significant ($p < .001$). This change represented the largest magnitude in shift across the six weeks.

A repeated measures ANOVA with a Greenhouse-Geisser correction determined that mean coping differed statistically significantly between time point, $F(4.042, 4.109) = 6.288$, $p < .001$, $\eta^2 = .03$. Examination of within subject contrasts indicated that a quadradic shape of change most adequately characterized the data, $F(1, 13.746) = 20.856$, $p < .001$, $\eta^2 = .09$. Post-hoc tests revealed that the COVID-19 disruption elicited an increase in students reports of their ability to cope with academic and broader life challenges from week 10 of the semester to week 13 (2.860 ± .07 vs. 3.205 ± .06, respectively), which was statistically significant ($p < .001$). Post-hoc tests using the LSD correction also revealed that the COVID-19 disruption elicited a decrease in coping from week 13 of the semester to week 15 (3.205 ± .06 vs. 2.957 ± .06, respectively), which was statistically significant ($p = .005$). These two changes represented the largest magnitudes in shift across the six weeks.

A repeated measures ANOVA with a Greenhouse-Geisser correction determined that mean reports of feelings of depletion differed statistically significantly between time points, $F(4.208, 3.870) = 4.761$, $p < .001$, $\eta^2 = .02$. Examination of within subject contrasts indicated that a quadradic shape of change most adequately characterized the data, $F(1, 8.907) = 10.887$, $p < .001$, $\eta^2 = .04$. Post-hoc tests revealed that the COVID-19 disruption elicited an increase in depletion from week 12 of the semester to week 15 (3.411 ± .06 vs. 3.748 ± .08, respectively), which was statistically significant (p < .001). This change represented the largest magnitude in shift across the six weeks (though weeks 11–15 were all statistically significantly smaller than week 15). See Table 3 for a summary of the means and standard deviations for each observation. See Figure 3 for a summary of managing, coping, and depleted findings.

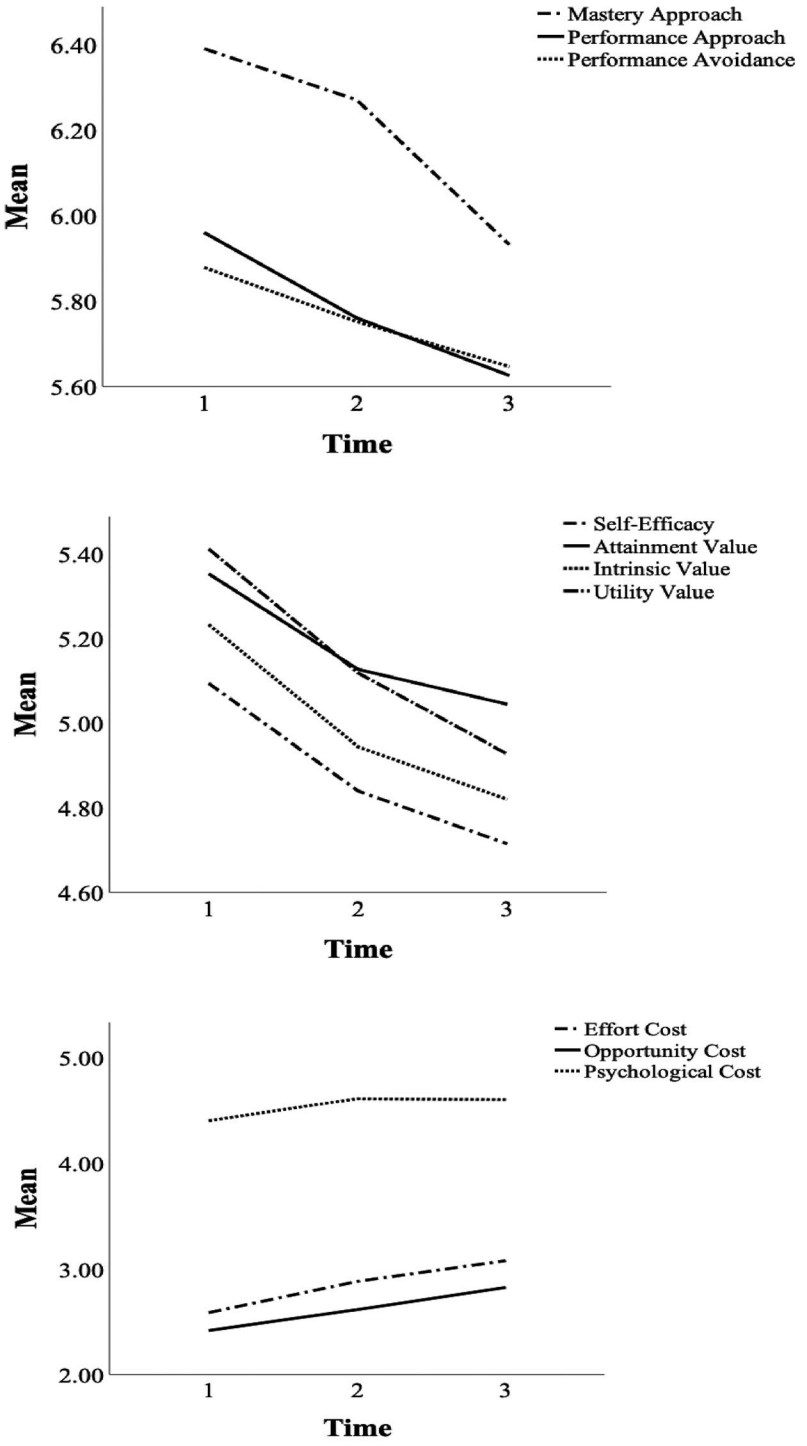

Figure 2. Mean ratings to motivation for learning questionnaire scales by time.

RQ3: patterns in open ended responses and prediction of final course grade

After students' responses to open-ended items were submitted to LIWC analyses and metrics were derived to represent the amount or proportion of their writing that indicated use of terms representing specific dictionaries, a backward selection regression analysis was conducted to

Table 3. Means and standard deviations for managing, coping, and depleted variables.

	Week 10		Week 11		Week 12		Week 13		Week 14		Week 15	
	M	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*
Managing	2.98	0.96	3.03	0.89	3.16	0.78	3.07	0.81	3.20	0.86	3.08	0.92
Coping	2.86	1.00	3.10	0.90	3.10	0.83	3.21	0.85	3.10	0.92	2.98	0.95
Depleted	3.50	1.17	3.52	0.96	3.41	0.93	3.43	0.98	3.53	1.09	3.75	1.12

Note. n = 226.

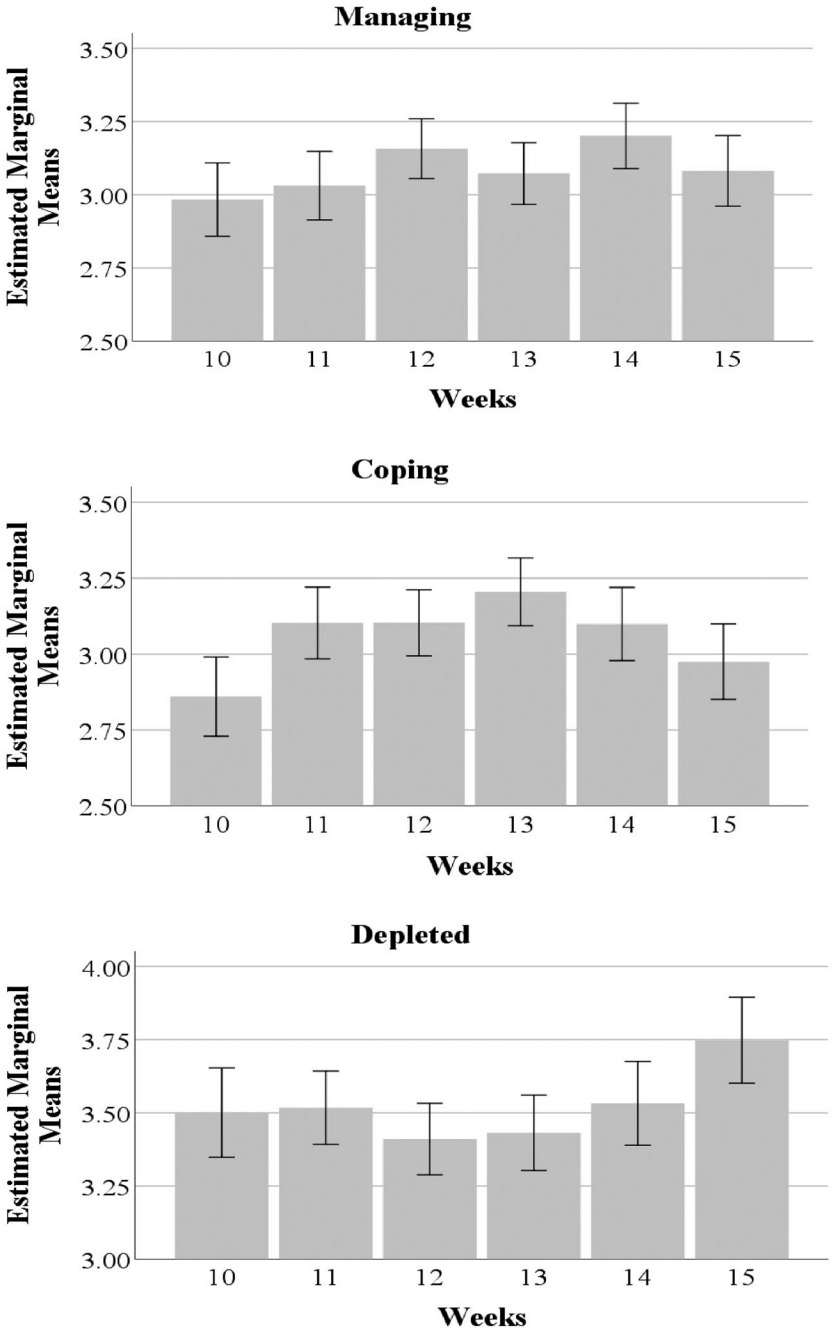

Figure 3. Summary of managing, coping, and depleted repeated measures ANOVAs.

predict final course grade from the linguistic inquiry and word count categories, motivations, and reports of coping, management, and depletion. The software carried out 10 iterations of variable removal, producing a final model accounting for a significant amount of variation in final course grade, $R^2 = .175$, $F(6, 1555.160) = 7.747$, $p < .001$. The overall adjusted R-square increased during the backward selection process ($\Delta R^2 = .002$). The final parsimonious model included the linguistic inquiry categories "anger" and "family," feeling depleted in week 10 of the semester (i.e., the first week after remote instruction, and opportunity cost, self-efficacy, and effort cost reported at Time 2 (i.e., the onset of remote instruction). Table 4 depicts the final regression model. Table 5 provides example responses from the linguistic inquiry categories that were retained in the final model.

Discussion

The results describe a pattern of self-regulated engagement that, when it could be enacted, increased student success. During the COVID-19 disruption, students who were able to maintain high levels of self-efficacy and make necessary sacrifices to support their learning were able to perform well in the course. Feelings of mental depletion, increased costs, and affective feelings of anger and increased familial demands were related to poor academic performance. The results support models of self-regulation that highlight the role of motivation and external demands in execution of learning strategies (Ben-Eliyahu & Linnenbrink-Garcia, 2015; Schunk & Greene, 2018). The findings also support previous research that suggests under challenging circumstances students must often put aside learning goals in order to cope with unexpected or stressful situations (Boekaerts & Niemivirta, 2000). The findings speak to the need for additional research focused on how students respond to exogenous challenges during demanding learning tasks, and how both individuals' susceptibilities to challenges and resources to overcome them may vary across students. Below we discuss the study findings within the context of SRL theory, as well as describe the implications of the study for research on remote instruction.

Motivation and SRL

Repeated observation of students' motivations revealed that the shift to remote instruction induced what theorists would consider maladaptive levels and forms of academic motivation, and these largely persisted through the weeks following the disruption. Students self-reported lower mean levels of mastery approach and performance approach goals, lower self-efficacy, and that engagement in their course conferred lower intrinsic value, utility value, and attainment value, while also requiring greater cost to sustain engagement. This across-the-board drop in motivation and self-beliefs in conjunction with the rise in all forms of perceived cost indicate a maladaptive shift in motivation and beliefs.

Over the period of disrupted learning, student reports of management, coping, and depletion show a pattern of change over time that indicates students were increasingly struggling to regulate their behavior. Over the course of the last six weeks of the semester, students were more likely to report that they were managing their time poorly, culminating in week 14. Although students initially reported an increase in their ability to cope, this dropped off by week 13, creating a quadratic shape of change where students were least able to cope at the end of the semester. Student reports of an increasing inability to manage time and difficulty coping were accompanied by an accelerating increase in reported mental depletion, culminating at the end of the semester. These results support previous research that suggests control over learning is a finite resource that, when exhausted, can lead to decreases in motivation, self-regulation, and academic performance (Hagger et al., 2010). Clashing demands are often at the heart of depletion, and require people to make sacrifices to reach long-term goals (Baumeister & Vohs, 2007).

The idea that sacrifices are required to succeed under challenging academic circumstances was reflected by predictors retained in the final model. The final model indicated that students

Table 4. Summary of backward removal regression results predicting course performance.

	B	SE	Beta	t	Sig.	Cor	Partial	Part	Tol	VIF
(Constant)	74.74	8.61		8.68	0.00					
Depleted	−3.12	0.89	−0.24	−3.49	0.00	−0.30	−0.23	−0.21	0.79	1.27
Anger	−4.63	1.92	−0.15	−2.41	0.02	−0.20	−0.16	−0.15	0.90	1.12
Family	−3.66	2.12	−0.11	−1.73	0.09	−0.18	−0.12	−0.11	0.99	1.01
Self-efficacy	2.50	1.36	0.12	1.84	0.07	0.23	0.12	0.11	0.84	1.19
Effort cost	−1.66	0.76	−0.17	−2.18	0.03	−0.17	−0.15	−0.13	0.80	1.25
Opportunity cost	1.52	0.74	0.16	2.07	0.04	−0.02	0.14	0.13	0.92	1.09

Note. n = 226.

Table 5. Examples of open-ended responses scored in LIWC for use in regression model.

%Words flagged	Dictionary flagged
	Family
3.74	I wish the student made a petition asking for a A+ and the closure of the university during this crisis. Have three parents to worry about and my wife that still has to go to work.
3.08	Need to stay up later in the night so my family doesn't bother me. So I can better understand the material.
2.86	Stress levels are high as everyone in my family is laid off and emotionally we are in an unstable place.
2.65	I was forced to comeback home to California, there are a lot of COVID19 cases. Along with me coming home, my twin brother came home as well from out-of-state. With the added number of people home, I have to look for a job and help support my family due to the cut back of my mother's hours.
1.33	I liked in person lectures. It helps me to stay focused and there are much less distractions in a classroom rather than at home with everyone else in my family. The lecture was better for uninterrupted learning. Watching a video is not the same as an in person lecture. Being in person forces you to pay attention to the end.
1.32	It affected me a lot. One, time difference I am from Hawaii. Two, my access to the internet, which I have to go to my aunt's house to have an internet. Lastly, I feel more emotive being in class than online.
	Anger
5.88	Hate that it got switched to online. It's harder to focus.
3.08	Need to stay up later in the night so my family doesn't bother me. So I can better understand the material.
2.82	At first I thought it was going to suck but now I can pause/rewind the video so maybe its alright.
1.75	COVID-19 has disrupted the organized schedule I had of going to the library and having a good study routine. Now my brain has to disassociate me being at home with me being on vacation.
1.49	When I am at home, I feel less motivated to do work
1.08	Ever since this month started, coronavirus has affected my brain and really made me worry about my mom. she's a registered nurse so she's fighting this disease with patients every day in California, so it's very worrying for me. It's hard to study when the world is in shambles, so I haven't had as much time to study

Note. Data in the table represent the top six LIWC scores for each category. The prompt asked, "In a few sentences please elaborate on the ways the COVID-19 disruption has affected your approach to this course." The student responses have not been altered for readability.

who reported mental depletion early in the transition, who experienced feelings of anger, and increased family demands were more likely to perform poorly in the course. In contrast, students who maintained high self-efficacy and those who reported they made sacrifices to succeed were able to maintain higher levels of course performance. As cost is often associated with negative academic performance, future research should explore potential interactions between self-efficacy and perceptions of cost, where investments in learning paired with high self-efficacy may produce positive outcomes. This pattern of results has implications for the types of supports that may benefit students during times of disruption.

The best predictors of poor course performance were the affective variables underlying depletion, including anger and increased family demands. Visual inspection of the open-ended responses represented in the dictionaries retained in the model provide insights on specific events that characterize these experiences. Students reported concerns such as maintaining attention during online lectures, isolation during learning activities, and the need to engage with materials at odd times of the day or night. Text-mined indicators that predicted poor

achievement can focus educators on challenges that undermine students' motivation and engagement when academic tasks require rapid reorganization—particularly just after a disruption considering many of the predicators retained in the final model were those measured just after the transition to remote instruction. Particularly within the context of biology instruction, and other areas of the natural and physical sciences where tangible learning experiences (i.e., in the lab) have been moved to remote instruction, disruptions that require task redefinition may be particularly difficult for students when the schedules become chaotic, they are staying up late at night to work, and they are worrying about families or loved ones.

Study limitations

One limitation of the current study is that estimates of internal consistency cannot be calculated for the measures of coping, managing, and depletion. Although we followed best practices for creating single item measures, reliability estimates provide a ceiling for validity that cannot be assessed. Another limitation is that the study did not contain enough power for the use of MANOVA to protect against family-wise error rate; thus readers should be cautious about inflated risk of type 1 error for results with the smallest effect sizes. Further, it was not possible to generate a control or comparison group. As a result, we cannot experimentally determine if factors not related to the pandemic (e.g., the challenging nature of the course content; the difficulty of the exams) could have produced a similar result in a non-pandemic context. However, the content analysis of the open-ended responses (i.e., the LIWC findings) suggests that the pandemic played an important role in the pattern of findings, and provides a deeper understanding of the pandemic related sources of depletion for students.

Study implications

Going forward, as the potential for disrupted learning experiences remains high, instructors and designers can consider how to mitigate these challenges through instructional design efforts to provide a more sustainable digital learning experience for learners that can persist should future disruption occur. Students who experience extreme disruptions in their lives, during a pandemic or otherwise such as the death of a family member or experiencing trauma, may need additional supports to regulate their learning post disruptions to help them cope with required sacrifices due to familial demands, as well as instructional activities that support efficacy and encourage maintenance of learning goals. And finally, methodologically speaking, the understanding of the student experience using mined text can provide insights into the ways that exogenous factors, such as a disruption, specifically undermine motivation and engagement under new task conditions. The use of computer-assisted content analysis of open-ended responses is a useful method worthy of future research that can be used to improve triangulation, interpretation, and prediction, particularly in contexts were equivalent comparison groups are not feasible. Additionally, future research on the provision of supports that can mitigate feelings of depletion may help to improve student success, especially in challenging academic contexts. Institutions may wish to consider the effects of disruption on student learning (pandemic related or otherwise) and provide students with opportunities to support their self-regulatory capacities. Our results suggest these services should address students' ability to cope with external factors that affect their opportunity to succeed academically, increasing efficacy and limiting the need to make sacrifices.

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