Who's Stopping You? – Using Microanalysis to Explore the Impact of Science Anxiety on Self-Regulated Learning Operations

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Abstract

Research shows that anxiety can disrupt learning processes, but few studies have examined anxiety's relationships to online learning behaviors. This study considers the interplay between students' anxiety about science and behavior within an online system designed to support self-regulated science inquiry. Using the searching, monitoring, assessing, rehearsing, and translating (SMART) classification schema for self-regulated learning (SRL), we leverage microanalysis of self-regulated behaviors to better understand how science anxiety inhibits (or supports) different learning operations. Specifically, we show that while science anxiety is positively associated with searching behaviors, it is negatively associated with monitoring behaviors, suggesting that anxious students may avoid evaluation, opting instead to compensate with information-seeking. These findings help us to better understand SRL processes and may also help us support anxious students in developing SRL strategies.

Keywords: Education; e-learning; data mining; science anxiety; learning technology; self-regulated learning; self-efficacy

Introduction

As a basic human emotion, anxiety refers to an ensemble of cognitive, affective, somatic arousal, and behavioral components, evoked in response to mental representations of a threat or danger in the environment (Zeidner, 2014). In educational contexts, test anxiety may be the most commonly discussed form of anxiety (Zeidner, 2007), but research has also considered anxiety surrounding specific subjects or fields (Mallow & McDermott, 1988), including science anxiety – the focus of this work.

Students suffering from science anxiety are often calm and productive in nonscience courses, including mathematics, but experience anxiety in science classes. Science anxiety is distinct from general anxiety (Mallow & McDermott, 1988) and can be caused by an array of sources, including lack of role models, gender/racial stereotyping, and the stereotyping of scientists in the popular media (Udo et al., 2004). Female students can be especially affected, and some research indicates that female students are significantly more likely to experience science anxiety than their male peers (Udo et al., 2004). Research suggests a number of short term (e.g., lower self-efficacy) and long term (e.g., avoiding certain careers) effects of science anxiety (Udo et al., 2004).

Anxiety has also been linked to avoidance behaviors (Middleton & Midgley, 1997) and task-level performance and behavior (Eysenck et al., 2007). Neuroscience research has shown that anxiety can enhance neural patterns associated with error detection (Moser et al., 2013), which can prove advantageous in some learning contexts. However, anxiety is also thought to inhibit both working memory (Wu, 2018) and the goal-directed attention system (Eysenck et al., 2007). Further investigations into attentional control suggest anxiety often inhibits students' efficiency more than their performance (Eysenck et al., 2007). Theoretically, this suggests that anxiety limits students' ability to use prior knowledge/expectations to monitor their progress on current goals (Corbetta & Shulman, 2002; Eysenck et al., 2007) – a crucial underpinning to self-regulated learning (SRL).

At a high level, SRL is a process in which learners take initiative to identify their learning goals and then regulate their learning strategies, cognitive resources, motivation, and behavior to optimize their learning outcomes (Pekrun et al., 2002; Winne, 2017). Since it was first characterized by Zimmerman (1989), SRL's essential role in learning has become well established (Klug et al., 2011). Indeed, Dent & Koenka's (2016) recent meta-analysis found that SRL practices were moderately correlated with academic achievement (r=0.20) and science outcomes specifically (r=0.26). Prior work has also examined the relationship between science anxiety and measures of SRL, but those measures have often been collected with self-report (e.g., Tärning et al., 2017), which can be susceptible to presentation effects, and may be particularly unreliable in this case given anxiety's negative impacts on cognition and reasoning.

In classrooms, teachers may employ several techniques to support anxious students (Finlayson, 2014), but learning technologies are often self-led environments with minimal external supports (Azevedo et al., 2010). Students must instead use SRL tactics to allocate their time and complete the learning task. As such, it is important to understand how anxiety influences SRL within learning technology.

This study examines the impact of science anxiety on how students interact with Betty's Brain, a learning-by-teaching tool for middle school science. Through a study of 99 sixth-graders, we examine how science anxiety relates to student behavior, performance, and perceptions of the learning technology. We examine student behavior through the lens of the COPES and SMART models of SRL (Winne, 2017). The COPES model classifies elements of SRL into five categories: Conditions, Operations, Products, Evaluations, and Standards). In this work, we categorize all student actions recorded in the logs as "operations" within the COPES model (defined as "cognitive and behavioral actions applied to perform the task"). We then further subcategorize these *operations* using Winne's (2011) SMART model, which distinguishes operations based on their inputs and the products generated (more detail below).

To our knowledge, this paper presents the first exploration of the relationship between anxiety and SRL behaviors within learning technology. Through this approach, we provide detailed insight into the learning methods a student is employing as well as understanding how effective these methods may be.

Methods

This study explores the relationship between measures of science anxiety (adapted from Betz, 1978) and students self-regulatory behaviors (Winne, 2017) within the open-ended computer-based learning environment Betty's Brain.

Betty's Brain Platform

Betty's Brain uses a learning-by-teaching model (Biswas et al., 2004), where students must teach a virtual agent named Betty by creating a causal map of a scientific process (e.g., climate change). Betty shows her "learning" by taking quizzes that are graded by a mentor agent, Mr. Davis. As students construct Betty's map, they must navigate various learning resources, including hypermedia resources and a teaching manual that explains how to represent causal reasoning. In this open-ended system, students choose how they build their maps, how often they quiz Betty, and how often they interact with Mr. Davis, who supports their learning and teaching efforts (Biswas et al., 2016).

Betty's Brain is a suitable environment for studying SRL behaviors for two reasons. First, students choose when and how to perform each step of the learning process (both their own and Betty's). Indeed, the Betty's Brain's pedagogical agents are designed to facilitate the development of SRL behaviors by encouraging the gradual internalization of effective learning strategies. Second, students' interactions are logged with detailed timing information, enabling the microanalysis of student actions (Siadaty et al., 2016) for the measurement of SRL strategies.

Anxiety Measure

Science anxiety was measured using an adapted version of the math anxiety survey (MAS): a ten-item survey that uses a six-point Likert scale. MAS was chosen since it is suitable for younger learners (Johnston-Wilder et al., 2014) and has high test–retest reliability (Pajares & Urdan, 1996). We adapted questions to refer to science topics instead of mathematics (Figure 2), and responses were averaged to yield a final science anxiety score between 1 and 6.

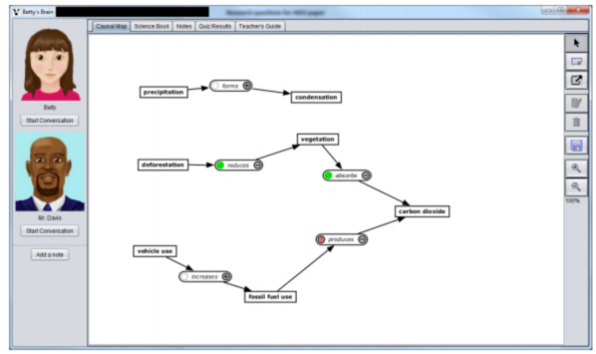

Figure 1. A partial causal map in Betty's Brain

Original MAS	"Mathematics makes me feel uncomfortable and nervous"
Modified	"Science makes me feel uncomfortable and nervous"

Figure 2. Example of modification to MAS items

Measures of Self-Regulated Learning

We study SRL in the context of the COPES, and subsequent SMART, models of SRL. The COPES model, grounded in information processing theory, characterizes SRL as a series of events that happen over recursive stages. These stages are (1) task definition, (2) goal setting and planning, (3) studying tactics, and (4) metacognitively adapting studying techniques. Each stage is then characterized by Conditions, Operations, Products, Evaluations, and Standards (COPES). Further work from Winne provided additional subcategories within the COPES model – the SMART model of operations (Winne, 2017). The SMART model presents a more detailed approach, categorizing operations into five kinds of activities: searching, monitoring, assembling, rehearsing, and translating.

We assigned each of the possible student actions within Betty's Brain (see above) to one of the SMART categories, paying particular attention to student agency. Betty's Brain requires students to decide when to look for information and how to build, refine, and test their causal map, but some quizzes, for example, are system-initiated. Each category is briefly described below, and specific examples are given; for more details, see (Winne, 2011, 2017).

Searching. Learners who are searching choose to focus their attention on a particular knowledge base or resource to update working memory (e.g., search the virtual textbook).

Monitoring. Learners who are monitoring evaluate their perceptions compared to available standards (e.g., reviewing quiz feedback).

Assembling. Learners who are assembling connect new knowledge items to networks of prior knowledge, strengthening working memory (e.g., adding a causal link to the map).

Rehearsing. Learners who are rehearsing repeatedly direct attention to information they are currently working on to reinforce that information in working memory. Betty's Brain logged no rehearsing actions, so this category was not analyzed.

Translating. Learners who are translating reformat information into a new representation, creating the potential for alternate interpretations (e.g., taking notes about the readings).

We elected to categorize operations that added new items to the concept map within Betty's Brain as *assembling* and operations that edited existing items on the map as *monitoring*. However, we used student agency to help distinguish between *translation* and *monitoring* tasks. On the one hand, we determined that submitting a causal map for Betty to take a quiz (a student-initiated action) was *monitoring* because it was an action designed to elicit an evaluation. On the other hand, submitting a multiple-choice question – an evaluative action which requires a student to convert knowledge from the virtual textbook into a new format – was classified as either *monitoring* or *translation*, depending on whether the student or the system had initiated the action. That is, actions that were initiated by the system were classified as *translating* even if they had a strong evaluative component.

To operationalize these constructs, we leverage the timestamps logged for each action and calculate proportion of time spent on actions in each SMART category. We use time as out measure as opposed to number of actions in each category, as action counts did not necessarily reflect the amount of each category being performed. This was because some types of actions take considerably more time than others, this giving a misleading interpretation. For example, there are more monitoring actions than searching actions; however, it is common for students to spend considerably more time searching than monitoring. Thus, for analysis purposes, we calculated the time spent on each action instead of raw action counts.

We combine these with measures of knowledge, perceptual and motivational constructs, outlined in Table 1. We also included a measure of off-task behavior, calculated as the proportion of time which the student neither 1) viewed an information source for at least 30 seconds; nor 2) edited their map.

Data Collection

Data was collected at an urban Tennessee middle school, from 99 sixth-graders who used Betty's Brain in their regular science class. This school's population is 60% White, 25% Black, 9% Asian, and 5% Hispanic, with 8% enrolled in the free/reduced-price lunch program. Individual demographics were not collected.

Students used Betty's Brain to complete two science inquiry scenarios conducted in December 2018 and February 2019. In the first scenario, students spent four days (approx. 50 min/day) using Betty's Brain to complete a causal map about climate change. In the second scenario, students spent three days modeling thermoregulation. Students completed a pre-test of their prior knowledge before each scenario and an identical post-test after each scenario. Learning was then operationalized as post-test minus pre-test in both cases, yielding one learning score per scenario.

Items from the self-efficacy and task value scales (Table 1) were evenly split between the start and end of the first scenario (and later recombined). Finally, at the end of the second (thermoregulation) scenario, science anxiety surveys were administered alongside questions about students' perceptions of difficulty and familiarity of the topic and questions about Mr. Davis. Between the two scenarios, minor changes were made to Betty's Brain, including small changes to make Mr. Davis seem more polite. All other procedures were identical.

Table 1. Additional measures examined

Measure	Level	Type	Description
Pre/Post Test	Scenario	Test	Assessed *knowledge* of the current topic before and after Betty's Brain
Perc. Diff.	Scenario	Survey	Single Likert scale of students' *perceived difficulty* of each scenario
Perc. Fam.	Scenario	Survey	Single Likert scale of *perceived familiarity* with each scenario
Self-Efficacy	Student	Survey	Seven-item measure of *self-efficacy* derived from (Pintrich et al., 1991)
Task Value	Student	Survey	Five-item measure of *value of science* (Pintrich et al., 1991)
Off-Task Behavior	Scenario	Derived fr/ logs	Time spent *idle/disengaged* from the task (Segedy et al., 2015)

Results

Anxiety was approximately normally distributed, but a paired-samples *t*-test showed significant differences in prior knowledge for the two topics (climate change: M=6.24, SD=2.65; thermoregulation: M=5.74, SD=2.25; $t(98)=-10.64$, $p < 0.001$). Given these differences and known links between anxiety and performance (Mallow, 2006), we used a linear mixed-effects model (implemented in R with Bates et al.'s (2007) *lme4* package) to regress pre-test scores on anxiety and topic, with student as an intercept-only random effect. This approach was chosen due to the repeated (multiple sessions per student) and nested structure (sessions nested within students) of the data (Pinheiro & Bates, 2006). Because prior knowledge varied significantly as a function of the topic (p = .028) and anxiety (p = .001), we Z-scored both tests by topic and retained pre-test as a covariate in future models. Descriptive statistics for each variable in our analysis below (splitting by topic where appropriate) are shown in Table 2 and Table 3.

Table 2. Student-level descriptive statistics

	Mean	SD	Min	Max
Science Anxiety	2.41	0.69	1.00	4.40
Task Value	3.40	0.54	1.40	5.00
Self-Efficacy	2.38	0.46	1.29	4.28

Table 3. Topic-level descriptive statistics

	Climate Change				Thermoregulation			
	Mean	SD	Min	Max	Mean	SD	Min	Max
Student Perceptions								
Perceived Difficulty	2.82	1.09	1.00	5.00	2.47	1.25	1.00	5.00
Perceived Familiarity	3.80	0.94	1.00	5.00	2.10	1.15	1.00	5.00
Student Performance								
Pre-Test	6.32	2.65	2.00	13.00	5.81	2.25	1.00	13.00
Post-Test	9.28	3.28	2.50	17.00	10.22	4.34	2.00	21.50

Overview of Results

We first calculated correlations between science anxiety scores and other student measures. Table 4 gives these results separately for each scenario and shows that science anxiety is significantly correlated with prior knowledge (defined by pre-test) for both scenarios. Due to this, as well as the known impact of prior knowledge on student regulation and motivation (Winne, 2017), we also computed partial Spearman correlations that control for prior knowledge. Post-hoc *p*-value correction was conducted using the false discovery rate method.

Table 4. Spearman correlations with science anxiety across both scenarios and partial Spearman correlation controlling for pre-test (prior knowledge).

	Climate Change		Thermoregulation	
	Spearman	Partial	Spearman	Partial
Student Perceptions:				
Perc. Difficulty	-0.088	-0.091	**-0.361****	**-0.332****
Perc. Familiarity	**-0.286****	**-0.231***	-0.09	-0.084
Student Performance:				
Pre-Test	**-0.29****		**-0.244***	
Post-Test	-0.378**	**-0.258***	**-0.303****	**-0.23***
Learning	-0.168	**-0.258***	-0.2	**-0.23***
Proportion of Time:				
Off-task	0.128	0.066	0.136	0.1
Searching	0.144	0.155	0.235*	0.191
Monitoring	-0.184	-0.175	**-0.207***	**-0.209***
Assembling	-0.162	-0.032	-0.003	0.013
Translating	0.141	0.118	0.043	0.099

Note: Sig. findings in bold, *=p<0.05, **= p<0.01

We note that science anxiety was significantly related to the perceptual measures administered in this study, but was inconsistent across the scenarios. In the climate change scenario, anxiety correlated with lower familiarity, but correlated to lower difficulty in the thermoregulation scenario. These relationships held even when controlling for prior knowledge.

Although the thermoregulation finding is somewhat surprising, it suggests that anxious students felt more prepared to complete this (second) scenario. It's possible students' procedural familiarity with Betty's Brain influenced this perception. More research is required to test this hypothesis since procedural familiarity was not measured, but objective learning measures are compatible with this premise. Despite lower familiarity and lower pre-test scores in the thermoregulation scenario, the completion rate and post-test scores were higher for it than they were for the climate change scenario. In the climate change scenario, science anxiety was not significantly correlated to any of the behaviors labeled with the off-task model or SMART categories. However, in the thermoregulation scenario, science anxiety was positively correlated with searching behaviors and negatively correlated with monitoring behaviors. These relationships held when controlling for pre-test, meaning that the behavior differences are not attributable to low prior knowledge and instead warrant further investigation.

Student Motivation

We also correlated science anxiety to two motivation constructs – self-efficacy and task value – repeating our method of computing partial Spearman correlations to control for prior knowledge. The results indicated that students with higher science anxiety show lower self-efficacy. This finding is in line with similar findings for mathematics anxiety (Jameson & Fusco, 2014). We also observed that students with higher science anxiety placed a lower value on Betty's Brain tasks in ways that seem to align with avoidance strategies and/or reactions to a perceived external threat (Eysenck et al., 2007). Taken together, self-efficacy and task value form part of student motivation, implying that students with higher science anxiety are less likely to actively engage in science tasks.

Table 5. Spearman correlation between science anxiety and measures of self-efficacy and task value

	Spearman	Partial Spearman
Self-Efficacy	**-0.525****	**-0.488****
Task Value	**-0.329****	**-0.296****

Note. Bold values indicate a significant correlation, * = p < 0.05, ** = p < 0.01

Performance Measures

To further examine science anxiety's effect on student performance, we again constructed linear mixed-effects models for each performance measure (post-test or learning gains). Specifically, each model regressed a performance measure (*Z*-scored by topic) onto the students' science anxiety score, with student as an intercept-only random effect (which adjusts the model intercept per student) and student's pre-test score as a covariate. Perceived familiarity and off-task behavior were covariates in these models, but perceived difficulty was excluded to avoid suppressor effects. Table 6 gives standardized coefficients and shows anxiety negatively predicted student learning gains even when accounting for prior knowledge (via pre-test) and off-task behavior, which may also be influenced by anxiety (Mallow, 2006; Udo et al., 2004).

Table 6. Std β coef. regressing performance on anxiety

	Post Test	Learning
Pre-Test	**.42****	**.28****
Science Anxiety	**-.19****	**-.22****
Perceived Familiarity	.08	.09
Off-task Behavior	**-.14****	**-.18****

Note: Sig. findings in bold, *=p<0.05, **=p<0.01

Student Behavior/Self-regulation

Finally, we examined the relationship between anxiety and the five student behavior variables, namely the proportion of time spent off-task and the four SMART categories (Winne, 2017) found in our data. We again constructed linear mixed-effects models, with the same approach described above for each variable in turn. We included off-task behavior as a covariate in models predicting the SMART variables to avoid any potential confounds. Table 7 gives the resulting standardized beta coefficients.

Our results indicate that science anxiety influences how students use the system, specifically the degree to which they choose to engage in searching and monitoring behaviors. Searching involves reviewing "gold standard resources," whereas monitoring actions involve the student comparing their own work to external standards and making some kind of evaluation (e.g., "this is an accurate map of what I just read") (Winne, 2017).

Our results show that anxious students spend more time searching (relying on existing resources) and less time monitoring their work by reviewing feedback and/or making edits. When combined with performance measure results discussed above, these behavioral differences suggest that anxious students' ineffective self-regulation in the learning technology may be reducing their opportunities to learn. These results suggest that to facilitate online learning, we must acknowledge and address students' individual anxiety levels (discussed more below).

Table 7. Std β coef., regressing behavior on anxiety

	Dependent Variables				
	Off Task	Searching	Monitoring	Assembling	Translating
Pre-Test	-.09	-.09	.00	**0.2****	.15
Science Anxiety	.09	**.19****	**-.22****	-0.02	.01
Perc. Familiarity	.01	.06	-.07	0.01	.00
Off-task Behavior		**.15****	**-.19****	**-0.2****	.04

Note: Sig. findings in bold, *=p<0.05, **=p<0.01

Discussion and Conclusions

Science anxiety can impede a student who otherwise would excel, especially if it interferes with the increased use of online learning systems, which expect considerable use of SRL strategies.

Our results indicate that students with high science anxiety have low self-efficacy and low perception of task value. Notably, they ultimately performed worse while reporting lower levels of perceived difficulty, which may be related to how they self-assess their own abilities. That is, anxious students with low self-efficacy may not be able to adequately judge the difficulty of a particular learning context because they blame struggles on their own low skills. These effects were consistent even when controlling for factors like prior knowledge, demonstrating the clear impacts of science anxiety on student experiences.

We have also shown that science anxiety is linked to significantly different SRL behaviors, even when controlling for prior knowledge. Specifically, anxious students were more likely to spend their time searching for knowledge than monitoring/evaluating the work they have already completed. This finding aligns with work showing that anxious students avoid ego-threatening activities (Middleton & Midgley, 1997) and demonstrates an important mechanism underlying anxiety's to less learning. That is, if anxious students monitor their work less often, they are skipping important opportunities to reflect on feedback – a known precursor to learning (Pekrun et al., 2002) – and thus (unknowingly) limiting their learning experiences.

One key application of this work is the development of scaffolding for high-anxiety students. We have shown that anxious students are less likely to monitor their work. By analyzing student actions in real-time, we can follow their progress and provide additional guidance for high anxiety students. For example, we could have the mentor agent direct the student to a different task or evaluate their progress.

However, we should be mindful that students with high anxiety may be sacrificing their self-regulated learning techniques (i.e., *monitoring*) in order to better self-regulate their anxiety. That is, if monitoring behaviors invoke anxiety by forcing students to compare their performance to standards (potentially coming up lacking), encouraging such tasks directly may not be appropriate. Alternate approaches such as a human-the-loop design (i.e., the teacher) should instead be considered. On the other hand, if the primary connection between anxiety and lower educational performance is the avoidance of monitoring behaviors (as our results may suggest), nudges by the system or scaffolding students to participate in monitoring behaviors may help mitigate this problem.

Limitations and Future Work

Throughout this work we have relied on self-report measures, which in turn relies on students being cognizant of their own thinking and responding honestly. However, due to the highly internal nature of some of the constructs being measured, self-report presents the best viable option. To mitigate potential confounds, we leveraged a previously validated anxiety scale with reported high internal validity (Johnston-Wilder et al., 2014). One issue with our approach was that many of the self-reports happened only once during the study, either at the beginning or end. Future work should collect multiple reports throughout the learning session and perhaps also find ways to automatically detect some of the constructs and behaviors measured here, such as self-efficacy, task value, and perceived difficulty.

This work did not consider other factors (e.g., gender or general anxiety level) that may influence science anxiety. Future work should explore how such factors effect the interaction between anxiety and SRL.

In this work, we have used log file data to conduct a microanalysis of the operations part of the COPES model (Winne & Hadwin, 1998), categorizing the SRL behaviors using the subsequent SMART model (Winne, 2011). Future work should also consider broadening this approach to better represent the other COPES model elements, such as conditions and products. This more in-depth analysis will provide an even more detailed understanding of self-regulated learning within learning technologies and thus provide even greater potential to support students.

Concluding Remarks

This paper investigates the relationship anxiety has to the SRL strategies that students use in computer-based learning. Our analyses, focusing specifically on science anxiety, indeed showed that anxiety was related (if modestly) to students' SRL strategies, even after controlling for prior knowledge. These findings contribute to scientific understanding of anxiety in learning with technology and will inform practical implementations of efforts to reduce science anxiety. Reducing science anxiety is critical because of the adverse effects associated with it. Thus, we envision this paper ultimately contributing to better science learning and more positive perceptions of science.

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