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Anxiety, Achievement, and Self-Regulated Learning in CueThink

J. M. Alexandra L. Andres, University of Pennsylvania, aandres@upenn.edu
Ryan S. Baker, University of Pennsylvania, rybaker@upenn.edu
Stephen J. Hutt, University of Denver, stephen.hutt@du.edu
Caitlin Mills, University of Minnesota, caitlin.mills@unh.edu
Jiayi Zhang, University of Pennsylvania, jzhang7718@gmail.com
Sam Rhodes, CueThink, srhodes@cuethink.com
Allison DePiro, CueThink, adepiro@cuethink.com

Abstract: The effects of educational anxiety have been observed across multiple disciplines; anxiety negatively influences cognition, self-regulation, performance, and educational outcomes. However, there has been limited research on anxiety within the context of interactive learning environments. In the current research, we expand this by assessing whether and how trait-level anxiety (assessed as a pre- and post-measure in a year-long study) is related to students' self-regulated learning strategies, behaviors, belief, and achievement in the context of an open-ended math problem-solving platform, called CueThink. Results indicate that anxiety is negatively related to key constructs involving math achievement. Altogether, our findings generally imply that students with higher anxiety may avoid interacting with their stressors, in this case, math content, effectively contributing to poorer outcomes. We discuss our findings within the context of research and pedagogical and system design.

Introduction

Anxiety is generally defined as the affective reaction to overwhelming cognitive and motivational demands that are tied to highly valued academic situations (González, Fernández, & Paoloni, 2017; Pekrun & Perry, 2014; Zeidner, 2014) often resulting in decreased performance (Hong, 2010). Individuals prone to anxiety are purportedly less likely to effectively manage uncertainty leading to difficulties around decision making, which contributes to negative outcomes on performance, motivation, and attention across various subject areas (e.g., Ashcraft, 2002, Na, 2007; González et al., 2017; Pardo, Han, & Ellis, 2016; Taylor, & Fraser, 2013; Woolf et al., 2010). Anxiety around specific subject matter, such as math or science, can also lead to avoidance behaviors, both in daily life and within educational settings (Ashcraft, 2002; Brunye et al., 2013). This can then impact competence and academic success (Plake & Parker, 1982; Brunyé et al., 2013). When learners engage with a subject in which they experience anxiety, they are more likely to underperform as a result of hyper-focusing cognitive and attentional resources on apprehension and concern regarding the demands of an educational task instead of strategies for problem solving (Ashcraft, 2002; Beilock & Carr, 2005; Jelici et al., 2004).

Although previous research has established the impact of anxiety on learning, few studies have examined this phenomenon within the context of interactive learning environments (ILEs; with some exceptions, see Andres et al., 2021, Hutt et al., 2021b). As ILEs become more prevalent at all levels of education (Allen & Seaman, 2014) it is important that we consider how individual differences between students may impact their experiences, so that ILEs can be designed to better support students' needs. The effects of anxiety may also be compounded in ILEs where there may be reduced immediate feedback from instructors and increased demands of metacognitive skills, proficiency with technology and complicated software (Hsu et al., 2009). The fine-grained data collection by ILEs allows for insights into the interactions and relationships between learner cognition and affect (Hutt et al., 2021a; Sinha, Jermann, Li, & Dillenbourg, 2014). For example, extensive work has considered the relationship between learning, interaction and epistemic (or academically-relevant) affective states (e.g., boredom, confusion, delight, engaged concentration, and frustration) in ILEs. However, this work has generally not considered anxiety.

By better understanding how anxiety may manifest in ILEs, we gain not only a better understanding of the phenomena, but the potential to respond to and scaffold students experiencing anxiety. Affect-sensitive interventions have produced better learning gains (D'Mello & Graesser, 2012; Clavel & Callejas, 2015; DeFalco et al., 2018), and support positive self-perceptions and attitudes (Karumbaiah et al., 2017). Additionally, interventions have been designed to impact constructs such as motivation (De Vicente & Pain, 2002) and self-efficacy (Beal & Lee, 2005).

This paper thus examines the effects of anxiety within a digital learning application called CueThink, an open-ended math problem-solving platform. Specifically, this study leverages a multi-faceted correlational approach to understand what constructs are related to anxiety in the context of a math-focused ILE. Specifically, we collected a broad range of measures that may be related to anxiety in order to identify how anxiety relates to: 1) survey measures to identify how trait-level anxiety relates to changes in student usage, belief, achievement, learning, and performance; 2) previously-developed detectors of self-regulated learning behaviors; 3) usage behaviors in the ILE (e.g., response patterns and language). Through these analyses, we attempt to build a better understanding of how anxiety can influence learners within an ILE and how features of learner experiences can be used to eventually build systems that can identify and mitigate the influence of the effects of anxiety.

Methods

CueThink

CueThink is a digital learning application that scaffolds math problem-solving and encourages mathematical discourse through open-ended problems and corrective feedback. Students are asked to think aloud while they solve math problems to create a shareable screen-cast video of their overall problem-solving process as well as their final answer. Within CueThink, students work on Thinklets, step-by-step processes for solving math problems. Each Thinklet consists of four phases: Understand, Plan, Solve, and Review. This was developed in line with the Winne & Hadwin model of SRL (Winne & Hadwin, 1998) and scaffolds a problem-solving process that includes unpacking the problem, choosing a strategy, and creating a plan. Students can move freely across the four phases, including going back to a previous phase or skipping phases.

The Understand phase asks students to structure their conceptualization of the problem by asking three questions: (1) "What do you notice?" (2) "What do you wonder?" and (3) "What is your estimated answer to the problem?" In the Plan phase, students are asked to select strategies they will use to solve the problem (either from a pre-written list or self-defined) then write a plan on how they will use the strategies to solve the problem. In the Solve phase, students explain and present their answer. During this phase, the students create a screencast video using an interface that provides them with a whiteboard and mathematical tools (i.e., number lines, ruler, etc.). Lastly, in the Review phase, students provide the final answer to the math problem and reflect on the accuracy of their answer, the clarity of their responses, and record this reflection using checklists.

Once students have completed the problem, they share their screencast explanation for Peer Review. Teachers and peers are encouraged to annotate both the textual responses and video with the goal of prompting the student to identify their underlying reasoning or for using specific methods. These annotations are then sent back to the video's author for possible revision of the video.

Sample

A total sample of 213 of students (115 sixth grade and 98 seventh grade) participated in the larger study. However, as is common in classroom studies, not all students completed all measures. As a result, a varying number of students were included across statistical analyses in order to maximize the availability of data per analysis; final N's for each test are reported alongside the results in the following sections. All students were drawn from three middle schools from a large, suburban school district located on the West Coast of the United States. The participants identified their gender as male (40.8%), female (53.1%) or non-binary (1.9%) or other (2.8%), with 1.4% of participants electing not to specify a gender. The participants also identified as Hispanic/Latinx (29.6%), Middle Eastern (28.6%), 2 or more races (16.4%), Asian (6.6%), Black/African American (4.2%), or White (2.8%), with 11.7% of participants preferring not to specify their ethnicity.

Pre-test and post-test survey measures were administered within the course of this study (details below). Students were given approximately 75 minutes to complete three different survey components. The first was a paper-and-pencil mathematics assessment developed by Illustrative Mathematics (approx. 35 mins.), followed by an online set of questionnaires distributed over Qualtrics (approx. 20 mins). This form contained prompts from the modified Abbreviated Math Anxiety Scale, Indiana Math Belief Scale, i-Ready Diagnostic, and Junior Metacognitive Awareness Inventory. For consistency across the varied scales, each item from all self-report surveys were reported on a scale from 1-100. Lastly, the third component was Adaptive Cognitive Evaluation, to measure executive function (UCSF, 2022). The content of the pre-test surveys and post-test surveys were identical. The three components were administered in no particular order. Pre-test surveys were completed anytime within a two-week period between November and December 2021 and the post-tests were completed anytime within a three-week period in May 2022.

Research instruments

Executive Function. Executive function (EF) was measured using the Adaptive Cognitive Evaluation (ACE; Younger et al., 2022). ACE is implemented through a series of game-based cognitive tasks around three core EFs: inhibition, working memory (change detection), and cognitive flexibility (task switching; Miyake et al., 2000). Mean and standard deviation scores were calculated for both reaction time and accuracy measures.

Content Knowledge. i-Ready diagnostic assessments were used a proxy for mathematics content knowledge by the partnering district (Curriculum Associates, 2022). The i-Ready (CDE, 2022) instrument is an adaptive assessment tool used to identify math topics students are struggling with. It examines students' understanding of mathematical sub-domains, including numbers and operations, algebra, geometry, and measurement. This assessment was administered three times throughout the school year. These testing periods were conducted towards the beginning (September), middle (December to January), and end (May) of the academic year.

Metacognition. An abbreviated version of the Junior Metacognitive Awareness Inventory (MAI, Jr.; Rhodes et al., under review; Sperling et al., 2002) was administered to record subjective metacognitive and cognitive strategies applied by learners. Objective metacognition was separately recorded through the use of confidence judgements wherein students estimated how well they would perform on problem-solving exercises and would evaluate their performance immediately after the task. Scores for objective metacognition were calculated by computing the absolute value of the difference scores between an individual's confidence judgements and their actual performance.

Affective Instruments. Anxiety and mathematic epistemological beliefs were recorded using the modified Abbreviated Math Anxiety Scale (mAMAS; Carey et al., 2017), and belief scales 1, 5, and 6 of the Indiana Mathematics Beliefs Scales (IMBS; Kloosterman & Stage, 1992), respectively. The mAMAS uses a two factor structure that uses two subscales: learning math anxiety (Learning subscale), and math evaluation anxiety (Evaluation subscale; Hopko et al., 2003; Carey et al., 2017). The scale has shown good internal consistency, with an overall Cronbach's α 0.85, a Cronbach's α of 0.77 for the Learning subscale and Cronbach's α 0.79 for the Evaluation subscale (Carey et al., 2017; Cipora et al., 2015; Szczygieł, 2019). The scale was developed for children between 8 and 13 years old (i.e., overlapping with our research sample) and consisted of 9 items. The mAMAS was slightly modified to change adapt words to American English (e.g., "maths" to "math").

The IMBS measured beliefs around mathematics, more specifically about whether students believe they can solve time-consuming problems, about whether effort increases ability, and about the usefulness of mathematics in their lives, respectively. Students were also given five questions about their feelings about mathematics and the classroom and a question about how close they felt to the subject of mathematics. An abbreviated version of the IMBS (Rhodes et al., under review) was administered to reduce testing fatigue.

Problem Solving Measure. Members of the research team developed 3-item problem solving measures for each grade. All items for this measure were drawn from mathematics problems developed by Illustrative Mathematics (IM) and included in the current measure based on A) their cognitive demand and overall rigor, B) their alignment with district standards for the given grade level, and C) the degree to which students were required to explain their thinking. Each problem was scored for accuracy (IM accuracy) using IM answer keys. Problems were also scored by external researchers who assessed the degree to which a student demonstrated appropriate and sufficient mathematical understanding, regardless of their final answer (IM understanding). Each student received both scores.

Self-Regulated Learning Behaviors

In addition to these surveys, we also analyzed the relationship between anxiety and students' self-regulated learning (SRL) behaviors, using a set of behavior detectors developed using qualitative codes of SRL behaviors originally developed by Zhang and colleagues (2022) and validated for generalizability using 10-fold student-level cross validation (summarized in in Table 1). Results were calculated for each fold and averaged to yield one AUC ROC score per detector; all the values in the table show relatively high accuracy for each SRL behavior.

Table 1

Detector Performance Measured by AUC ROC with Standard Deviations (Zhang et al., 2022)

SRL Indicator	AUC ROC	Working Definition
Numerical Representation	0.894 (.078)	Representation notes numerical components and how these are used in the math problem
Contextual Representation	0.813 (.132)	Representation notes contextual details (setting/characters/situations) in the problem
Outcome Orientation	0.761 (.076)	Only a numerical estimate of the final answer (suggests a focus on output over process)
Data Transformation	0.815 (.163)	Information is manipulated to find a solution (suggests active problem solving)

Usage Data and Linguistic Features

Throughout this study, we extracted the amount of time each student spent completing tasks within each phase of their Thinklets. This data was recorded in seconds and summarized at the student level per phase (Understand, Plan, Solve, Review). Students' text responses were also analyzed for linguistic features using the Linguistic Inquiry and Word Count (LIWC) program (Pennebaker et al., 2015). LIWC analyzes 100 different lexical categories (Pennebaker et al., 2015) and uses a combination of computing methods and dictionaries that automatically tabulate text files for word counts and important psychosocial constructs and theories with words, phrases, and other linguistic constructions (Boyd et al., 2022). We attempted to minimize Type 1 errors by selectively choosing the lexical features under the *Cognition* category of LIWC (Boyd et al., 2022). This category reflects the different ways people refer to their thought processes. The table below summarizes the subcategories that are included in this category as well as some of the same words that are recorded and coded for each of these.

Table 2

LIWC categories and most frequently used exemplars (Boyd et al., 2022)

Subcategory	Most frequently used exemplars	Subcategory	Most frequently used exemplars
Cognitive Processes	but, not, if, or, know	Differentiation	but, not, if, or
Causation	how, because, make, why	Memory	remember, forget, remind, forgot
Discrepancy	would, can, want, could	Insight	know, how, think, feel
Tentative	if, or, any, something	All-or-None	all, no, never, always
Certitude	really, actually, of course, real	Number	one, two, first, once

Statistical Analyses

Spearman's Rho was used to correlate the survey-level and detector-based SRL behaviors with anxiety scores (pre-test and post-test scores). Spearman's Rho is commonly used in analyses where the assumptions of normality are not met. Linear regressions were used to regress interactions between anxiety scores and time spent in each phase onto measures of achievement, SRL behaviors, and linguistic features. Specifically, linear regression was used to examine the strength of the interaction of anxiety and time spent on the different outcome variables.

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Results

Correlations with Anxiety

Anxiety scores and survey measures were analyzed using Spearman correlations and Benjamini and Hochberg post hoc corrections (see Table 3). We find that pre-test and post-test anxiety positively correlate with one another ($\rho = 0.56$), where higher anxiety scores at the beginning of the school year corresponds to increases in anxiety scores later on in the school year. This is not surprising when considering the relative stability of trait anxiety. Higher anxiety before using CueThink is negatively correlated with math epistemological beliefs (IMBS scores) and achievement (iReady and IM scores), indicating that increased anxiety scores at the beginning of the study correspond to poorer mathematics performance and more negative beliefs around mathematics. A similar though less salient relationship can also be observed between post-texts of anxiety, as they negatively correlate to IMBS scores and achievement. The reduced effects of anxiety may potentially indicate that learners gain a better understanding of the requisites for solving mathematical problems throughout the study. Correlations between anxiety metrics and linguistic features were also conducted, however, did not yield any significant results.

Table 3

Spearman correlations for student level survey measures (p < .05, non-significant results were omitted from the table, red cells indicate negative correlations, blue cells indicate positive correlations)

	Anxiety (pre)	Anxiety (post)	jrMAI (pre)	jrMAI (post)	IMBS Solve (pre)	IMBS Solve (post)	MIBS Effort (pre)	IMBS Effort (post)	IMBS Useful (pre)	IMBS Useful (post)	iReady F2021	iReady W2022	iReady Sp2022	Overall iReady Avg.	IM accuracy (pre)	IM accuracy (post)	IM understand (pre)	IM understand (post)
Anx (pre)	1.00	0.56	-0.02	0.01	-0.36	-0.30	-0.27	-0.21	-0.29	-0.15	-0.28	-0.31	-0.24	-0.31	-0.25	-0.15	-0.23	-0.20
N	165	131	165	131	165	131	165	131	165	131	151	151	151	151	151	152	151	152
Anx (post)		1.00	0.05	0.07	-0.24	-0.27	-0.13	-0.19	-0.17	-0.10	-0.14	-0.23	-0.24	-0.22	-0.25	-0.01	-0.14	-0.07
N		134	131	134	131	134	131	134	131	134	127	127	127	127	121	133	121	133

Usage Data

Correlations and post hoc corrections were calculated to examine the relationship between the different survey responses and the amount of time students spent (in seconds) in the Review and Solve phase of their Thinklets. The results indicate that more time spent in these phases is associated with students engaging more frequently in specific SRL behaviors (see Table 4). Additionally, increased time spent in the Solve phase negatively correlates to math performance on the IM metric. The relationships indicate that despite the increased opportunity of students to engage in SRL behaviors, this may not necessarily correspond to improved performance.

Table 4

Correlations between time spent and survey responses and detectors (non-significant results were omitted from the table, red cells indicate negative correlations, blue cells indicate positive correlations)

	Time Spent (Review)	Time Spent (Solve)	Anx (pre)	Anx (post)	IM accuracy (pre)	IM accuracy (post)	IM understand (pre)	IM understand (post)	Numerical Rep.	Contextual Rep.	Outcome Orient.	Data Trans.
Time Spent (Review)	1	0.44	0.04	0.04	-0.18	-0.01	-0.04	0.03	0.33	0.09	0.23	0.11
N	179	179	165	134	153	156	153	156	179	179	179	179
Time Spent (Solve)		1	0.03	0.01	-0.24	0.04	-0.11	0.12	0.43	0.09	0.29	0.08
N		179	165	134	153	156	153	156	179	179	179	179

Linear regressions were also conducted to examine the influence of anxiety (pre-test and post-test) and time spent in the Solve phase, as well as their interaction, on outcomes of achievement and SRL behaviors. The regressions between pre-test anxiety scores and time did not reveal any significant relationships between the anxiety and the outcome variables. The linear regressions examining the interaction between post-test anxiety scores and time spent in the Solve phase on achievement and the SRL behaviors reveal that post-test anxiety had a significant interaction effect with time spent on Solve phase. A simple slopes analysis reveals that this interaction effect was predictive of increased math achievement ($p = .034$, $R^2 = .097$) where more anxious students who spend more time in the Solve phase are likely to perform better on their iReady scores where the students who take less time are more likely to perform worse. Urgency, perceived threats of failure, or avoidance (Dickerson & Kemeny, 2004; Chrousos, 2009) resulting from anxiety may lead to poorer performance on math tasks and metrics. Regressions were also conducted to predict linguistic variables using anxiety scores and time spent in the Solve phase; however, there were no significant results from this analysis.

Table 5
Beta Coefficients for Linear Regressions Predicting Achievement (N = 127) and SRL (N = 134) p < .05). Significant (p< 0.05) coefficients shown in blue and bold type

	Dependent Variables						Dependent Variables				
Predictors	iReady Avg	Numerical Rep	Contextual Rep	Outcome Orient	Data Transform	Predictors	iReady Avg	Numerical Rep	Contextual Rep	Outcome Orient	Data Transform
(Intercept)	**0**	0	**0**	**0**	**0**	(Intercept)	**0**	0	**0**	**0**	**0**
Anxiety (pre)	-0.28	0.02	-0.03	0.01	0.01	Anxiety (post)	**-0.2**	0.1	0.03	-0.02	0.1
Time Spent (Solve)	0.14	0.35	**0.16**	0.27	0.19	Time Spent (Solve)	0.13	**0.43**	0.28	0.23	0.23
Interaction (Anx (pre) * Time)	-0.08	0	-0.09	0.06	-0.06	Interaction (Anx (post) * Time)	**0.21**	-0.02	0.02	0.02	0.01

Discussion and Conclusions

The effects of anxiety within education are pervasive and diverse, however it remains to be comprehensively examined within ILEs. This work attempts to further research in this area by demonstrating the influences of anxiety on achievement, usage, and SRL within the CueThink platform. Overall, the combination of findings captures the influences of anxiety independently and in tandem with other significant interaction variables. Through this analysis, we found that higher pre-test anxiety corresponded to lower achievement scores within the math-based platform, and that a large proportion of the sample experienced anxiety. Though not a particularly surprising finding, these results are important in contextualizing the influence of anxiety within this kind of platforms and to better understand which aspects of the platform, usage, or content contribute to anxiety the most will be valuable to developing learning platforms that reduce student anxiety.

Further analysis shows that higher anxiety and changes in the time spent completing responses correspond to varying math achievement. More specifically, the results of this study indicate that students with increased levels of anxiety take more time in Solve phases but perform better on math-based assessments. Anxious students generally tend to avoid stress-inducing materials (Ashcraft, 2002; Brunyé et al., 2013), negatively impacting their academic outcomes (Plake & Parker, 1982; Brunyé et al., 2013). However, students who are able to overcome anxious reactions are also able to mitigate the effects of anxiety on their performance (Brunyé et al., 2013). The inclusion of time may aid in identifying anxious students and offer helpful interventions in response.

Overall, these results demonstrate the importance of student anxiety within ILEs. Our work seeks to highlight the differences in interaction that emerge among students based on their experiences of anxiety and how these, in turn, can impact various aspects of their learning experiences and outcomes. Future work should examine anxiety at the same level of the actions completed by students within the platform to support the development of automated detectors of anxiety. These detectors would support fine-grained analyses that can parse moment-by-moment experiences of anxiety and its influences on behavior, allowing educators, researchers, and designers to build anxiety-sensitive interventions to enhance educational experiences for anxious students.

References

Allen, I. E., & Seaman, J. (2014). *Grade change: Tracking online education in the United States*. Babson Survey Research Group.

Andres, J. M., Hutt, S., Ocumpaugh, J., Baker, R. S., Nasiar, N., & Porter, C. (2021). How anxiety affects affect: a QE investigation using affect detectors and data-targeted interviews. *In Int'l Conf. on Quantitative Ethnography* (pp. 268-283)

Ashcraft, M. H. (2002). Math anxiety: Personal, educational, and cognitive consequences. *Psy.Sci.,* 11, 181–185.

Beal, R., & Lee, H. (2005). Creating a pedagogical model that uses student self-reports of motivation and mood to adapt ITS instruction. *Workshop on Motivation and Affect in Educational Software.* Netherlands

Beilock, S. L., & Carr, T. H. (2005). When high-powered people fail: Working memory and "choking under pressure" in math. *Psy. Sci.,* 16, 101–105. http://dx.doi.org/10.1111/j.0956-7976.2005.00789.x.

Boyd, R. L., Ashokkumar, A., Seraj, S., & Pennebaker, J. W. (2022). The development and psychometric properties of LIWC-22. Austin, TX: University of Texas at Austin.

Brunyé, T. T., Mahoney, C. R., Giles, G. E., Rapp, D. N., Taylor, H. A., & Kanarek, R. B. (2013). Learning to relax: Evaluating four brief interventions for overcoming the negative emotions accompanying math anxiety. *Learning and Individual Differences*, 27, 1-7.

Carey, E., Hill, F., Devine, A., & Szűcs, D. (2017). The modified abbreviated math anxiety scale: A valid and reliable instrument for use with children. *Frontiers in Psychology*, 8, 11.

Chrousos, G. P. (2009). Stress and disorders of the stress system. *Nature Reviews Endocrinology*, 5(7), 374-381.

Cipora, K., Szczygieł, M., Willmes, K., & Nuerk, H. C. (2015). Math anxiety assessment with the AMAS: Applicability and usefulness: Insights from the Polish adaptation. *Frontiers in Psychology,* 6, 1833

Clavel, C., & Callejas, Z. (2015). Sentiment analysis: from opinion mining to human-agent interaction. *IEEE Transactions on Affective Computing, 7*(1), 74-93

CDE. (2022). i-Ready Diagnostic. https://www.cde.state.co.us/uip/i-ready-assessment-description

Curriculum Associates (2022). Research base for i-Ready Personalized Instruction for Mathematics: Executive Summary.

D'Mello, S. Graesser, A. (2012). Dynamics of affective states during complex learning. *Learning & Instruction*, 22, 145-157.

Dickerson, S. S., & Kemeny, M. E. (2004). Acute stressors and cortisol responses: a theoretical integration and synthesis of laboratory research. *Psychological Bulletin*, 130(3), 355.

De Vicente, A., & Pain, H. (2002). Informing the detection of the students' motivational state: an empirical study. In *Int'l Conf. on Intelligent Tutoring Systems* (pp. 933-943). Springer, Berlin, Heidelberg.

DeFalco, J. A., Rowe, J. P., Paquette, L., Georgoulas-Sherry, V., Brawner, K., Mott, B. W., Baker, R. S., & Lester, J. C. (2018). Detecting and addressing frustration in a serious game for military training. *Int'l Journal of Artificial Intelligence in Education, 28* (2), 152- 193.

González, A., Fernández, M. V. C., & Paoloni, P. V. (2017). Hope and anxiety in physics class: Exploring their motivational antecedents and influence on metacognition and performance. *J. R. Sci. T.*, *54*(5), 558-585.

Hong, Z. (2010). Effects of a collaborative science intervention on high achieving students' learning anxiety and attitudes toward science. *International Journal of Science Education*, 32, 1971–1988.

Hopko, D. R., Mahadevan, R., Bare, R. L., and Hunt, M. K. (2003). The abbreviated math anxiety scale. *Assessment* 10, 178. doi: 10.1177/1073191103010002008

Hunter, L. E., Meer, E. A., Gillan, C. M., Hsu, M., & Daw, N. D. (2019). Excessive deliberation in social anxiety. *BioRxiv*, 522433.

Hutt, S., Ocumpaugh, J., Andres, J. M., Alexandra, L., Munshi, A., Bosch, N., … & Biswas, G. (2021). Who's stopping you?–Using microanalysis to explore the impact of science anxiety on self-regulated learning operations*. Proceedings of the 42nd Annual Meeting of the Cognitive Science Society.*

Hsu, M. K., Wang, S. W., & Chiu, K. K. (2009). Computer attitude, statistics anxiety and self-efficacy on statistical software adoption behavior. *Computers in Human Behavior, 25*(2), 412–420.

Jelici, M., Geraerts, E., Merckelbach, H., & Guerrieri, R. (2004). Acute stress enhances memory for emotional words, but impairs memory for neutral words. *Int'l Journal of Neuroscience, 114*(10), 1343-1351.

Karumbaiah, S., Lizarralde, R., Allessio, D., Woolf, B. P., Arroyo, I., & Wixon, N. (2017). Addressing student behavior and affect with empathy and growth mindset. *Proc.10th Int'l Conf. on Educational Data Mining*

Kloosterman, P., & Stage, F. K. (1992). Measuring beliefs about mathematical problem solving. School Science and Mathematics, 92(3), 109–115. https://doi.org/10.1111/j.1949-8594.1992.tb12154.x

Kim, B., Zyromski, B., Mariani, M., Lee, S. M., & Carey, J. C. (2017). Establishing the factor structure of the 18-item version of the junior metacognitive awareness inventory. *Measurement & Evaluation in Counseling and Development, 50*(1-2), 48-57.

Malik, S. (2015). Undergraduates' Statistics Anxiety: A Phenomenological Study. *Qualitative Report,* 20(2).

Miyake, A., Friedman, N. P., Emerson, M. J., Witzki, A. H., Howerter, A., & Wager, T. D. (2000). The Unity and Diversity of Executive Functions and Their Contributions to Complex "Frontal Lobe" Tasks: A Latent Variable Analysis. Cognitive Psychology, 41(1), 49–100. https://doi.org/10/bkksp2

Na, Z. (2007). A study of high school students' English learning anxiety. *The Asian EFL Journal, 9*(3), 22-34.

Pardo, A., Han, F., & Ellis, R. A. (2016). Combining university student SRL indicators and engagement with online learning events to predict academic performance*. IEEE Trans. on LT, 10*(1), 82-92.

Pekrun, R., & Perry, R. (2014). Control-value theory of achievement emotions. In R. Pekrun & L. Linnembrink-Garcıa (Eds.), *International Handbook of Emotions in Education* (pp. 120–141).

Pennebaker, J. W., Boyd, R. L., Jordan, K., & Blackburn, K. (2015). *The Development and Psychometric Properties of LIWC2015.* Mahwah, NJ: Erlbaum.

Plake, B. S., & Parker, C. S. (1982). The development and validation of a revised version of the Mathematics Anxiety Rating Scale. *Educ. and Psy. Measurement,* 42(2), 551-557.

Rhodes, S., Bryck, R., and Gutierrez de Blume, A. (under review.). Exploring factors influencing mathematics problem solving. Proceedings of the *45th Annual Mtg. of the North American Chapter of the International Group for the Psychology of Mathematics Education* (PME-NA).

Sinha, T., Jermann, P., Li, N., & Dillenbourg, P. (2014). Your click decides your fate: Inferring information processing and attrition behavior from MOOC video clickstream interactions. *Emp. Meth. in NLP: Workshop on Modeling Large Scale Soc. Int. in MOOCs.* http://www.aclweb.org/anthology/W14-4102

Sperling, R. A., Howard, B. C., Miller, L. A., & Murphy, C. (2002). Measures of children's knowledge and regulation of cognition. *Contemporary Educational Psychology,* 27, 51–79.

Sperling, R. A., Richmond, A. S., Ramsay, C. M., & Klapp, M. (2012). The measurement and predictive ability of metacognition in middle school learners. *J. of Educ. Research*, 105, 1–7.

Stage, F. K., & Kloosterman, P. (1992). Measuring beliefs about mathematical problem solving. *School Science & Mathematics, 92*(3), 109-115.

Szczygieł, M. (2019). How to measure math anxiety in young children? Psychometric properties of the modified Abbreviated Math Anxiety Scale for Elementary Children (mAMAS-E). *Polish Psy. Bulletin*, 50(4).

UCSF. (2022). Ace Explorer. *Neuroscape.* https://neuroscape.ucsf.edu/researchers-ace/

Winne, P. H. (2017). Learning analytics for SRL. *Handbook of Learning Analytics*, 754, 241-249.

Winne, P.H. and Hadwin, A.F. (1998). Studying as SRL. *Metacog in Educ. Theory & Practice.* 277–304.

Younger, J., O'Laughlin, K., Anguera, J. A., Bunge, S., Ferrer, E. E., Hoeft, F., McCandliss, B., Mishra, J.,

Rosenberg-Lee, M., Gazzaley, A., & Uncapher, M. (2022). Better together: Novel methods for measuring and modeling development of executive function diversity while accounting for unity. PsyArXiv. https://doi.org/10.31234/osf.io/ctzwx

Younger, J., O'Laughlin, K., Anguera, J. A., Bunge, S., Ferrer, E. E., Hoeft, F., McCandliss, B., …& Uncapher, M. (2022). Better together: Novel methods for measuring and modeling development of executive function diversity while accounting for unity. PsyArXiv. https://doi.org/10.31234/osf.io/ctzwx

Zeidner, M. (2014). Anxiety in education. In R. Pekrun & L. Linnenbrink-Garcıa (Eds.), *Int'l Handbook of Emotions in Education* (pp. 265–288). New York: Routledge.

Zhang, J., Andres, J. M., Alexandra, L., Hutt, S., Baker, R. S., Ocumpaugh, J., Mills, C., … & Young, T. (2022). Detecting SMART model cognitive operations in math problem-solving process. *15th Int. Conf. Educ. Data Mining*.