Predicting Student Participation in STEM Careers: The Role of Affect and Engagement during Middle School

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Given the increasing need for skilled workers in science, technology, engineering, and mathematics (STEM), there is a burgeoning interest to encourage young students to pursue a career in STEM fields. Middle school is an opportune time to guide students' interests towards STEM disciplines, as they begin to think about and plan for their career aspirations. Previous studies have shown that detectors of students' learning, affect, and engagement, measured from their interactions within an online tutoring system during middle school, are strongly predictive of their eventual choice to attend college and enroll in a STEM major (San Pedro et al., 2013; 2014). In this study, we extend prior work by examining how the constructs measured by these detectors relate to the decision to participate in a STEM career after college. Findings from this study suggest that subtle forms of disengagement (i.e., gaming the system, carelessness) are predictive and can potentially provide actionable information for teachers and counselors to apply early intervention in STEM learning. In general, this study sheds light on the relevant student factors that influence STEM participation years later, providing a more comprehensive understanding of student STEM trajectories.

Keywords: STEM participation, affect detection, knowledge modeling, educational data mining

1. INTRODUCTION

Over the past decades, there has been an increasing demand for science, technology, engineering, and mathematics (STEM) graduates in the workforce. From 2004 to 2008, the average annual increase in employment for science and engineering fields was twice as high as occupations in other fields (Wang, 2013). Consistent with this trend, the U.S. Bureau of Labor Statistics (2014) projected an employment growth rate of 18.7% for occupations related to science and engineering from 2010 to 2018, and a lower growth rate of 14.3% for all other occupations. These employment trends suggest that there will be greater opportunities for students if they emerge from their studies with significant math and science training. However, the current pipeline for STEM graduates has been deemed to be inadequate in meeting the needs of building a STEM workforce. According to the 2012 President's Council of Advisors on Science and Technology (PCAST), the proportion of freshmen who intended to major in science and engineering fields has only increased by 7.2% from 1998 to 2008. Additionally, the proportion of bachelor's degrees related to natural science and engineering has remained between 15% to 17% from 2000 to 2011. Given that STEM participation is growing more slowly than STEM opportunities, this shortage of students pursuing science or math studies motivates the need to increase STEM participation in young students.

In an effort to generate greater interest in STEM careers, many schools seek to initiate programs that will entice young students to pursue STEM-related majors and enter the STEM workforce. Previous research suggests that these STEM programs are most effective if they take place before high school, even as early as middle school (Kneztek et al., 2013). Middle school has been shown to be an important juncture for guiding students' motivation and interests in STEM careers. It is during middle school that students develop work habits, a sense of self-efficacy, and thoughts of career explorations (Bleeker & Jacob, 2004). Middle school is also a critical time to develop student's motivation, as middle school is a point where many students tend to disengage from school (Ruiz, 2012). Extreme forms of disengagement (i.e., low attendance or misconduct) and academic failure in 6th grade have been found to be strongly predictive of never graduating high school, thereby affecting opportunities for postsecondary education and post-college employment (Balfanz, Herzog, & Mac Iver, 2007). As such, it may be valuable to investigate which student factors in middle school are connected to the decisions that lead to eventual participation in STEM disciplines.

Prior research has revealed that several factors are associated with the decision to pursue STEM fields, including a student's gender, ethnicity, SAT Math score, grades (Crisp, Nora, & Taggart, 2009) and parental education (Gruca, Ethington, & Pascarella, 1988). In a longitudinal study using three Institute of Educational Sciences IES datasets, Chen and Weko (2009) found that the proportion of STEM entrants was higher among students who were male, Asian/Pacific Islander, foreign, belonging to families with higher income, and with higher GPA than students who did not have these characteristics.

Other studies have focused on exploring the impact of socio-cognitive factors on STEM participation. According to evidence reviewed in Lent, Brown, and Hackett's (1994) Social Cognitive Career Theory, occupational interests were found to be substantially correlated with self-efficacy, a dynamic set of self-beliefs specific to capabilities to perform in a specific domain, and outcome expectations, beliefs about the consequences of performing particular actions. In general, empirical evidence suggests that self-efficacy is predictive of career-related interests, achievement, persistence, and career exploratory behaviors (cf. Lent, Brown, & Hackett, 2000). In relation to this, Bandura and colleagues (2001) found that 6th and 7th graders' perceived academic self-efficacy was associated with judgments of whether they could be efficacious in the medical field, which, in turn, influenced them to choose a career aspiration as a doctor, nurse, or pharmacist a year later. A recent systematic literature review about STEM career development noted that ability beliefs and self-efficacy, along with parent and teacher knowledge and affective stereotypical values about STEM major choices, are important for building career interests and career development in children ages 8 to 16 (van Tujil & van der Molen, 2016).

In addition to this, Reinhold, Holzberger, and Seidel (2018) recently conducted a systematic literature review of 28 studies focusing on school effects on STEM orientation, which is comprised of career interest, career goals, and choice actions concerning the career goal. Researchers presented a theoretical framework with the following variables: school-level variables, which included school ecology (e.g., school composition) and school leadership, policies, and organization (e.g., characteristics of personnel teaching STEM courses); and classroom-level variables, which included classroom ecology (e.g., class composition), and attributes of teachers. They found that a combination of factors predicts STEM orientation.

While these studies offer actionable information about the relation between socio-cognitive factors and pathways towards STEM careers, it may be possible to collect measures of individuals' cognitive and socio-emotional development in a more reliable and rapid fashion than the types of measures used in these studies such as surveys. Due to the challenges of social

desirability effects in self-assessments, some aspects of children's cognitive and socio-emotional factors may also be better captured through more automated measures.

With the rise of digital educational software in classrooms across the U.S., researchers have developed automated detectors of student learning, affect, and engagement from their online behaviors to predict postsecondary outcomes. For example, San Pedro and colleagues (2013) applied fine-grained models of student learning, affect, and behavior to data from students using blended learning software during their middle school years and then tracked those students to the end of their high school years and their eventual decision of whether or not to enroll in college. They found that several features related to student learning (i.e., probability of student knowledge, correct answers, and the number of problems started in the tutoring system), affect (i.e., confusion and boredom), and disengaged behavior (i.e., carelessness, gaming the system) significantly predicted whether or not a student would eventually enroll in college. Specifically, learning was associated with a higher probability of college enrollment, gaming the system was associated with a lower probability of college enrollment, carelessness was associated with a lower probability of college enrollment after controlling for student knowledge, and boredom and confusion were associated with a lower probability of college enrollment.

San Pedro and colleagues (2014) found that a subset of these same set of detectors could also predict STEM major enrollment. Specifically, they found that the probability of knowledge and gaming the system were significant predictors of whether or not a student decides to enroll in a STEM major, with students who game the system being less likely to enroll in STEM. In concert, the findings of these two studies present evidence that early indicators of a student's learning and engagement are associated with their eventual decision to enroll in college and major in STEM fields.

In this study, we extend this previous work by investigating the relationship between students' learning, affect, and engagement in middle school and their decision to participate in a STEM career post-college. The decision to participate in STEM fields is a longitudinal process that builds from experiences in middle school, which carries into decisions during postsecondary education and employment after college. Understanding how students' early learning, affect, and disengaged behavior influence their eventual choices of occupation will help provide a more comprehensive picture of student pathways towards STEM fields. In order to this, we conduct our study using a dataset of 467 participants who used an online learning platform around a decade ago and for whom we have information as to whether they are currently working in a STEM or non-STEM field. In this paper, we investigate the differences between participants who eventually participate in a STEM field versus a non-STEM field in relation to their learning, affect, and disengaged behavior using specific educational software in middle school. We discuss how these features related to learning, affect, and engagement can provide potential implications for educational interventions to better support students toward STEM participation.

2. ASSISTMENTS SYSTEM

The present study focuses on student outcomes related to participation in STEM careers using the log files within ASSISTments (Heffernan & Heffernan, 2014). The ASSISTments platform is a free online formative assessment and tutoring system for middle school students. While ASSISTments can be used in a range of domains, it is primarily used for mathematics. Teachers use ASSISTments to assessstudents' knowledge of mathematical concepts and skills while facilitating their learning of these concepts. The system provides teachers with formative assessments of thestudents' learning progress in their acquisition of specific

knowledge components within a mathematics topic. Currently, the ASSISTments platform has been adopted by 650 teachers across the United States, with an average of over 5,000 student users a day and over 50,000 student users a year

The ASSISTments system maps specific problems to the knowledge of certain math skills. For most main problems (i.e., the original problem a student encounters), students have the opportunity to access hints or scaffolding questions. Hints provide a sequence of clues that explain to students how to solve an original problem. The last hint in each hint sequence (called the bottom-out hint) provides students with the answer to the original problem. Scaffolding questions break down the original problem into individual steps. These scaffolds are answered in a linear progression, where students must correctly answer the first scaffolding question in order to proceed to the next one. Once all scaffolding questions are completed, students may be prompted to answer the original question again.

3. DATA

3.1. POST-COLLEGE SURVEY DATA

This study's data consisted of a sample of individuals who had used the ASSISTments tutoring system in middle school and had agreed to participate in later research around their post-high school academic and career achievement (e.g., San Pedro et al., 2014).

As U.S. college graduates often use LinkedIn as a job search platform, LinkedIn information was used as a metric for STEM career achievement. In 2017, a research partner of the ASSISTments team used a Premium LinkedIn account to search for and determine the type of post-college employment (including graduate school as a form of employment) for the participants in (San Pedro et al., 2014). The job indicated in each participant's personal LinkedIn account was coded to reflect participation in a STEM or non-STEM career. STEM career was defined as jobs related to the fields eligible for National Science Foundation STEM funding (National Science Foundation, 2015). The rest of the jobs, as well as unemployment, were defined as participation in a non-STEM career. This information was collected around five months after students could have been expected to graduate from college for the second cohort of students in the sample (17 months for the first cohort). LinkedIn information was not collected for students whose profiles indicated that they had not yet graduated from college. Career and interaction log data were obtained for 467 students, 35% of the students in the overall sample that had enrolled in college. This proportion was moderately lower than the national average use of LinkedIn, which is 51% for recent U.S. college graduates (Perin & Anderson, 2019). However, this lower rate is almost certainly because not all students in the sample graduated on time – less than half of U.S. undergraduates graduate within four years (U.S. DOED NCES, 2019).

This data set was released for use by researchers in fully deidentified form through the ASSISTments Data Mining competition (Patikorn, Heffernan, and Baker, this issue) and was used for analysis in the present study.

3.2. ASSISTMENTS LOG DATA

We obtained log files of student interactions with the ASSISTments platform for these 467 students, consisting of their use of ASSISTments in middle school courses between 2004 to 2007. These 467 students generated 271,074 actions across a total of 3078 original and

scaffolding problems. On average, each student encountered about 243 ASSISTments problems. Knowledge, affect, and behavior detectors were applied to this dataset to create measures of each student construct.

4. EXISTING DETECTORS OF KNOWLEDGE, AFFECT, AND BEHAVIORS

In order to analyze which student factors influence STEM career participation, we leveraged existing detectors previously developed and validated for ASSISTments, which included models of student knowledge, affect (boredom, engaged concentration, confusion, frustration), disengaged behaviors (off-task, gaming the system, carelessness) and information about student usage of the system (total number of first responses to problems in the tutor as a proxy for overall usage). As in San Pedro et al.'s previous work (2013, 2014), these detectors were applied to each student action in the current dataset. Table 1 provides a summary of the goodness of fit of these detectors, originally published in (Baker et al., 2010; San Pedro et al., 2013; Pardos et al., 2013).

4.1. STUDENT KNOWLEDGE

Estimates of student knowledge were computed using the Bayesian Knowledge Tracing Model (Corbett & Anderson, 1995), which has been extensively used in intelligent tutoring systems to estimate student latent knowledge based on their observable opportunities to apply a given skill. Specifically, BKT updates the estimated probability a student knows a skill each time he or she makes the first response to a new problem. It uses the following four parameters for each skill, keeping each parameter constant across students and contexts: 1.) L_0, the initial probability that the student knows the skill before starting work in the learning system, 2.) T, the probability of learning the skill at each opportunity to apply it, 3.) G, the probability of obtaining a correct answer despite not knowing the skill, and 4.) S, the probability of giving an incorrect answer despite knowing the skill (Corbett & Anderson, 1995). Estimates of student knowledge using BKT were calculated at each student's first response to each problem and were applied without modification to each subsequent attempt on that same problem (in other words, learning due to completing a problem was assumed to occur between problems rather than between incorrect answers on the same problem). BKT model parameters were calculated using a brute-force grid search on the 2004 to 2007 ASSISTments data logs (cf. Baker et al., 2010).

4.2. AFFECT AND DISENGAGED BEHAVIORS

To obtain assessments of student affect and behavior, four detectors of students' affective states (i.e., boredom, engaged concentration, confusion, and frustration) and three detectors of disengaged behaviors (i.e., off-task, gaming, and carelessness) were used in this study. These detectors of affect and disengaged behaviors are identical to the models used in previous studies (e.g., San Pedro et al., 2013; 2014). A two-stage process was used to develop all of these detectors, except for carelessness, which will be discussed in the following section. Student affect and behavior labels were first created from field observations using the BROMP protocol and HART Android app (Ocumpaugh et al., 2015), followed by the synchronization of these labels with ASSISTments log data occurring at the same time as or shortly before (within 20 seconds) field observations being recorded. All detectors were better than chance at identifying

each construct in unseen students and were at the state of the art for affect detection at the time they were developed (see discussion in San Pedro et al., 2013). Detector confidences were rescaled to reduce bias produced by re-sampling in the training sets, in the same fashion as in the previous use of these detectors (San Pedro et al., 2013; 2014).

After implementing the two-stage process, these detectors were then applied to the student actions in the current dataset in order to obtain confidence values for the presence and absence of each student construct.

4.3. CARELESSNESS

Our analysis also included a measure of carelessness, calculated as the probability of careless errors, where the student has the knowledge of the skill to answer correctly but gives an incorrect answer to the problem (Clements, 1982). Carelessness is operationally defined using the Contextual Slip model, which contextually estimates the probability that, despite a student knowing a skill, he or she will produce an incorrect answer. In this model, the probability of carelessness and slip is assessed contextually, accounting for differences depending on the behavioral context of the student error. Errors might come after several slow correct responses on the same skills, or these might come after a hint request. In other words, the estimate of carelessness/slip is likely to vary based on the features of the student action and behavioral context in which it occurs, including the speed of the action and student's history of helping-seeking behaviors from the tutor. As a result, the carelessness probability estimate is different for each student action. In this study, we utilize a carelessness model previously developed for ASSISTments (San Pedro et al., 2013). This model was built using a linear regression algorithm with six-fold student-level cross-validation to evaluate how well the model generalizes to new students drawn from the same population used for the study. As a result, this carelessness model is able to make numerical predictions of the probability that a student action is a careless error each time a student makes the first attempt on a new problem step.

Table 1: Performance of original affect and behavior detectors

Detector	Algorithm	AUC	Kappa	r
Carelessness	Linear regression			0.458
Student Knowledge	BKT	0.758		
Boredom	JRip	0.632	0.229	
Engaged Concentration	K*	0.678	0.358	
Confusion	J48	0.736	0.274	
Frustration	Naïve Bayes	0.682	0.324	
Off-task	REP-Tree	0.819	0.506	
Gaming	K*	0.802	0.370	

5. METHODS AND RESULTS

In this paper, we examined how student knowledge, affect, and learning compared between two groups, students who took a STEM job after college and those who did not. As a first step, confidence values from existing detectors were aggregated (averaged) to create overall estimated proportions of knowledge, affective states, and behaviors for each student. We then conducted a set of independent samples t-tests to compare mean group differences in the

proportions of knowledge, affect, and engagement, as well as the total number of first actions in the tutor. The Benjamini-Hochberg method (Benjamini & Hochberg, 1995) was used to adjust the alpha values for multiple t-test comparisons. If the homogeneity of variances was violated, as assessed by Levene's test for equality of variance, the Welch t-test was used. As shown in Table 2, we found that the differences of mean proportions for student knowledge, carelessness, and gaming the system were statistically significantly different between the two groups. On average, students who eventually chose a STEM career ($M = 0.082$, $SE = 0.009$) had significantly lower proportions of gaming the system compared to their counterparts who did not pursue a STEM career ($M = 0.112$, $SE = 0.007$), Welch t (243.74) = -2.57, $p = 0.011$, adjusted alpha = 0.017, Cohen's $d = 0.33$. As expected, we found higher mathematics knowledge for the group who pursued a STEM-related job ($M = 0.292$, $SE = 0.015$) than the group who did not ($M = 0.224$, $SE = 0.007$), Welch t (174.95) = 4.05, $p < 0.0001$, adjusted alpha = 0.011, Cohen's $d = 0.61$. The same pattern of results was found for carelessness, as in San Pedro et al. (2013). Students who pursued a STEM-related career after college ($M = 0.154$, $SE = 0.007$) had significantly higher proportions of carelessness than students who did not ($M = 0.120$, $SE = 0.004$), Welch t (174.53) = 4.19, $p < 0.0001$, adjusted alpha = 0.006, Cohen's $d = 0.63$.

There was the initial appearance of a marginally significant difference in the mean proportions of frustration between students who pursued a STEM-related career and students who did not, with lower proportions of frustration during use of ASSISTments in the group that pursued a STEM career ($M = 0.120$, $SE = 0.005$) compared to the group who did not ($M = 0.129$, $SE = 0.003$). However, this finding did not hold up after applying the Benjamini-Hochberg post-hoc correction, t (465) = -1.74, $p = 0.082$, adjusted alpha = 0.022, Cohen's $d = 0.16$. No other significant differences were found for the other affective states or behaviors.

Table 2: Features for Students Who Participated in STEM Careers Post-College (1, $n = 117$) and did not participate in STEM Careers Post-College (0, $n = 350$)

Feature	STEM Career	Levene's test	Mean	Std. Dev.	Std. Error Mean	t-value	Cohen's d
Carelessness	1	$p < 0.05$	0.154	0.079	0.007	4.193	0.63
	0		0.120	0.067	0.004	$p < 0.0001$*	
Student Knowledge	1	$p < 0.05$	0.292	0.163	0.015	4.047	0.61
	0		0.224	0.138	0.007	$p < 0.0001$*	
Boredom	1	$p = 0.213$	0.253	0.032	0.002	0.034	0.00
	0		0.253	0.035	0.002	$p = 0.973$	
Engaged Concentration	1	$p = 0.065$	0.651	0.025	0.002	1.131	0.10

	0		0.648	0.030	0.002	$p = 0.259$	
Confusion	1	$p = 0.806$	0.106	0.037	0.003	-0.081	0.01
	0		0.106	0.040	0.002	$p = 0.935$	
Frustration	1	$p = 0.264$	0.120	0.053	0.005	-1.742	0.16
	0		0.129	0.049	0.003	$p = 0.082$	
Off-task	1	$p = 0.202$	0.220	0.076	0.007	0.196	0.02
	0		0.219	0.086	0.005	$p = 0.845$	
Gaming	1	$p < 0.01$	0.082	0.102	0.009	-2.569	0.33
	0		0.112	0.127	0.007	$p < 0.05*$	
Total first responses	1	$p = 0.69$	289.590	175.857	16.258	1.061	0.10
	0		269.500	177.684	9.498	$p < 0.287$	

*Significant after Benjamini-Hochberg correction

Considering the non-intuitive finding between students' carelessness and their participation in their STEM career, we decided to further investigate the influence of this disengaged behavior on STEM participation. Previous research found that carelessness in middle school becomes negatively associated with college attendance when student knowledge is taken into account (San Pedro et al., 2013). As such, we attempted to investigate whether the same finding will be replicated when predicting the decision to participate in a STEM career.

In order to do this, we built a multiple logistic regression model to predict whether or not a student pursued a STEM-related career from his or her student knowledge and carelessness in a tutoring system used in middle school. We choose a logistic regression analysis due to our dichotomous dependent variable, which indicates whether or not a student participated in a STEM-related career after college. This statistical approach also matches previous work investigating the relationship of disengaged behaviors and long-term outcomes (San Pedro et al., 2013). The logistic model predicts the logit of the outcome, which is the natural logarithm of an odds ratio of the outcome occurring, given a set of predictor variables (Peng, Lee, & Ingersoll, 2002). To compute for the odds ratio in a logistic model, we divide the odds ratio of an outcome occurring with the presence of predictor variables by the odds ratio of an outcome occurring without these predictors. If the odds value is greater than 1.0, this indicates that an increase in the predictor increases the odds of the outcome occurring. Conversely, if the odds value is less than 1.0, this indicates that an increase in the predictor decreases the odds of the outcome occurring.

Table 3 shows the results of our logistic regression models with carelessness only and a combination of carelessness and knowledge. When carelessness is taken by itself, it is shown to be positively predictive of student participation in a STEM career. When a student becomes more careless, the odds that he or she pursues a STEM-related job also increases, $\chi2 (1) = 18.607$, $p < 0.0001$. However, once we control for student knowledge, carelessness is no longer a significant predictor of pursuing a STEM-related job after college, $\chi2 (1) = 1.127$, $p = 0.288$. These results suggest that the effects of carelessness are confounded with knowledge when predicting long-term outcomes related to STEM careers, possibly a result of the common measurement framework used for both. However, we did not obtain the result found in San Pedro et al. (2013), where carelessness flipped sign and was negatively associated with college enrollment after controlling for knowledge, a pattern seen in other research as well (Baker et al., 2010). One possible explanation is that the negative relationship between carelessness and student outcomes, strong enough to appear in other (shorter-term) analyses, was no longer strong enough in this longer-term analysis to overcome carelessness's relationship with the (positively correlated) knowledge.

Table 3: Logistic Models of Participation in a STEM Career from Carelessness Only and Carelessness and Knowledge

	β	S.E.	Wald	Df	Sig.	Exp(B)
Carelessness	6.175	1.431	18.607	1	$p < 0.0001$	480.535
Constant	-1.934	0.230	70.634	1	$p < 0.0001$	0.145
Carelessness	5.415	5.101	1.127	1	0.288	224.653
Student Knowledge	0.388	2.502	0.024	1	0.877	1.475
Constant	-1.930	0.231	69.600	1	$p < 0.0001$	0.145

We also examined possible effects between students' knowledge and the other feature that had a significant independent *t*-test result: gaming the system. To study this, we ran a logistic regression model with gaming only, followed by a model involving both gaming and knowledge. As seen for findings around carelessness, gaming the system is no longer significantly predictive of whether or not a student will pursue a STEM career, when controlling for students' knowledge, $\chi2 (1) = 0.384$, $p = 0.536$. These findings suggest that carelessness and gaming the system both interact with STEM career outcomes in a fashion connected to knowledge. Whether knowledge drives both these behaviors/affective states and STEM career outcomes, or whether knowledge moderates or mediates the relationship between the behavior/affect and STEM career outcomes, cannot be clearly established from these findings alone, and represents an important area for future investigation.

Table 5: Logistic Models of Participation in a STEM Career from Gaming Only and Gaming and Knowledge

	β	S.E.	Wald	Df	Sig.	Exp(B)
Gaming	-2.340	1.029	5.177	1	$p < 0.05$	0.096
Constant	-0.871	0.140	38.667	1	$p < 0.0001$	0.418
Gaming	-0.687	1.110	0.384	1	0.536	0.5030
Student Knowledge	2.712	0.781	12.060	1	$p < 0.0001$	15.063
Constant	-1.724	0.291	35.094	1	$p < 0.0001$	0.178

6.   DISCUSSION AND CONCLUSION

Due to the increasing needs for STEM workers, there has been increasing interest in examining what predicts student pathways towards STEM fields. Previous studies have examined the role of students' knowledge, affective states, and engagement in a math tutoring system in a middle school on college attendance (San Pedro et al., 2013) and choice of college major (San Pedro et al., 2014). In this study, we have built on previous work to investigate whether a student's knowledge, affect, and engagement also influence the decision to pursue a STEM career after college. We use LinkedIn data to investigate students' career choices. This choice of measure makes it much easier and less intrusive to collect data than traditional longitudinal follow-up methods, which often involve extensive protocols involving phone calls, voicemails, emails, instant messaging, text messaging, Skype, and offering participation through any of these mediums plus several office locations for in-person data collection (Vincent et al., 2012). However, the data source used in this paper does lead to a lower response rate than more intensive procedures, which may create validity risks around selection bias.

As previously discussed, we found significantly higher mathematics knowledge among students who pursued a STEM-related career than those who did not. This finding aligns with previous work, which showed significantly higher mathematics knowledge among students who attended college (San Pedro et al., 2013) and students with STEM majors (San Pedro et al., 2014), compared to their counterparts. These results suggest that developing aptitude in middle school math is positively associated with the decision to enroll in college, pursue a STEM major, and participate in a STEM career after college. These findings align with Wang's (2013) theoretical model, which indicates that high achievement and developing the aptitude for math and science during schooling is associated with the intent to pursue STEM fields.

In addition, previous work has shown that students who game the system are less likely to enroll in college (San Pedro et al., 2013) or choose a STEM-related college major (San Pedro et al., 2014). As such, lower proportions of gaming the system in students who eventually pursued STEM careers post-college is not surprising. However, this negative relationship does not remain statistically significant once we take into account students' knowledge, measured concurrently by ASSISTments. This may be because once we remove students with low

knowledge, the remaining students' gaming behaviors are not significantly predictive of their choice to pursue STEM careers. Alternatively, it may be that knowledge moderates or mediates the relationship between gaming the system and STEM careers. For instance, if gaming the system were to lead students away from STEM careers by reducing their knowledge, we would not see an independent relationship once controlling for knowledge. Previous studies have shown negative correlations between gaming the system and learning (Cocea, Hershkovitz, Baker, et al., 2009) and later performance on standardized examinations (Pardos et al., 2013). On one hand, gaming the system may be negatively related to the likelihood of pursuing a STEM-related career by reducing mathematics knowledge. Tutor interventions, such as changing the incentive structure for gaming (Baker et al., 2006) and inviting students to reflect on their progress in between problems (Arroyo et al., 2007), have been shown to reduce the frequency of gaming and enhance learning. On the other hand, gaming the system may be an indicator of a student's lack of interest in STEM. In this case, gaming would be a side effect, rather than directly causing lower participation in STEM. While the reasons behind a student's lack of interest in STEM are likely complicated, providing actionable information about gaming would still help teachers identify struggling middle school students who are less likely to enroll in college, choose a STEM major, and pursue a STEM career. Although the relationship between gaming the system and later STEM careers is not entirely straightforward, gaming the system remains early evidence of lower attainment and participation. Future work is needed to understand the interactions between gaming and knowledge and the degree to which the relationship between gaming the system and the decision to pursue a STEM job post-college is causal.

Our results also showed a counterintuitive relationship between carelessness and participation in a STEM career post-college. Taken by itself, carelessness is found to be more common among students who decide to pursue a STEM-related job than other students. San Pedro and colleagues (2013) found the same pattern of results in their study, with a positive relationship between carelessness and college enrollment. However, when controlling for student knowledge, they found that carelessness flips directions and it becomes negatively associated with college attendance. We examined whether this finding replicates in our current study. Results from a multiple logistic regression revealed that carelessness is no longer significantly predictive of participation in a STEM career when controlling for the effects of student knowledge. However, the link between carelessness and STEM career participation remains positive rather than flipping sign. These findings, along with previous literature, suggest that the association between carelessness and the decision to enroll in college and participate in a STEM career is confounded with student knowledge in middle school. The impact of carelessness on student outcomes appears to persist over five years but not over a decade; in either case, carelessness and student knowledge should be considered together rather than in isolation. As noted in San Pedro et al. (2013), carelessness appears to be the disengaged behavior of more successful students.

In summary, this study emphasizes the vital role of STEM experiences during middle school in supporting student pathways towards STEM disciplines. As previous work has revealed student factors associated with the choice to enroll in college and select a college major, this study reveals which factors of student learning, affect, and behaviors are associated with the choice to participate in a STEM career college, providing a more comprehensive picture of STEM trajectories. Such findings may have potential implications in providing a new perspective for teachers and counselors to promote meaningful STEM experiences and assess students' learning and engagement. For instance, our findings suggest that it may be valuable for teachers and counselors to consider gaming the system as an indicator of subtle

disengagement, and to take into account students' level of knowledge when evaluating these forms of evidence as well as their careless errors. In addressing extreme forms of disengagement (e.g., fist fights, cutting class, etc.), interventions are often applied far too late, making it difficult for teachers to manage students' disruptive behaviors. The subtle forms of disengagement studied in this paper provide more actionable information for early intervention, as these help teachers and counselors identify which students are likely struggling in the classroom before their disengagement becomes potentially more disruptive later on. Recent findings show that alerts about students' gaming behaviors in tutoring systems led to more teacher time allocated for interventions and students' higher posttest scores (Holstein, 2018). As such, this work suggests that these effects may have longer-standing benefits than previously realized. Ultimately, this study indicates that relatively mild and subtle forms of disengagement or negative experience may play a substantial role in a student's trajectory away from a STEM career. This evidence indicates that action to address this disengagement – whether in an automated fashion or provided by a teacher – is warranted.

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REFERENCES

ARROYO, I., FERGUSON, K., JOHNS, J., DRAGON, T., MEHERANIAN, H., FISHER, D., ... & WOOLF, B. P. (2007, June). Repairing disengagement with non-invasive interventions. In *AIED* (Vol. 2007, pp. 195-202).

BAKER, R. S., CORBETT, A. T., GOWDA, S. M., WAGNER, A. Z., MACLAREN, B. A., KAUFFMAN, L. R., ... & GIGUERE, S. (2010, June). Contextual slip and prediction of student performance after use of an intelligent tutor. In *International Conference on User Modeling, Adaptation, and Personalization* (pp. 52-63). Springer, Berlin, Heidelberg.

BAKER, R. S., CORBETT, A. T., KOEDINGER, K. R., EVENSON, S., ROLL, I., WAGNER, A. Z., ... & BECK, J. E. (2006, June). Adapting to when students game an intelligent tutoring system. In *International Conference on Intelligent Tutoring Systems* (pp. 392-401). Springer, Berlin, Heidelberg.

BALFANZ, R., HERZOG, L., & MAC IVER, D. J. (2007). Preventing student disengagement and keeping students on the graduation path in urban middle-grades schools: Early identification and effective interventions. *Educational Psychologist*, *42*(4), 223-235.

BANDURA, A., BARBARANELLI, C., CAPRARA, G. V., & PASTORELLI, C. (2001). Self-efficacy beliefs as shapers of children's aspirations and career trajectories. *Child Development*, *72*(1), 187-206.

BENJAMINI, Y., & HOCHBERG, Y. (1995). Controlling the false discovery rate: a practical and powerful approach to multiple testing. *Journal of the Royal Statistical Society: Series B (Methodological)*, *57*(1), 289-300.

BLEEKER, M. M., & JACOBS, J. E. (2004). Achievement in math and science: Do mothers' beliefs matter 12 years later?. *Journal of Educational Psychology*, *96*(1), 97.

CHEN, X., & WEKO, T. (2009). Students who study science, technology, engineering, and mathematics (STEM) in postsecondary education (NCES 2009-61). Washington, DC: National Center for Education Statistics.

CLEMENTS, M. A. (1982). Careless errors made by sixth-grade children on written mathematical tasks. *Journal for Research in Mathematics Education*, 136-144.

COCEA, M., HERSHKOVITZ, A., & BAKER, R. S. (2009). The impact of off-task and gaming behaviors on learning: immediate or aggregate?. In *Proceeding of the 2009 Conference on Artificial Intelligence in Education: Building Learning Systems that Care: From Knowledge Representation to Affective Modelling*. IOS Press.

CORBETT, A. T., & ANDERSON, J. R. (1995). Knowledge tracing: Modeling the acquisition of procedural knowledge. *User Modeling and User-Adapted Interaction*, *4*(4), 253-278.

CRISP, G., NORA, A., & TAGGART, A. (2009). Student characteristics, pre-college, college, and environmental factors as predictors of majoring in and earning a STEM degree: An analysis of students attending a Hispanic Serving Institution. American Educational Research Journal, 46(4), 924–942.

GRUCA, J. M., ETHINGTON, C. A., & PASCARELLA, E. T. (1988). Intergenerational effects of college graduation on career sex atypicality in women. Research in Higher Education, 29(2), 99–124.

HEFFERNAN, N. T., & HEFFERNAN, C. L. (2014). The ASSISTments Ecosystem: Building a platform that brings scientists and teachers together for minimally invasive research on human learning and teaching. *International Journal of Artificial Intelligence in Education*, *24*(4), 470-497.

HOLSTEIN, K., MCLAREN, B. M., & ALEVEN, V. (2018). Informing the design of teacher awareness tools through causal alignment analysis. *In J. Kay and R. Luckin (Eds.). Proceedings of the 13th International Conference of the Learning Sciences* (pp. 104-111).

KNEZEK, G., CHRISTENSEN, R., TYLER-WOOD, T., & PERIATHIRUVADI, S. (2013). Impact of Environmental Power Monitoring Activities on Middle School Student Perceptions of STEM. *Science Education International*, *24*(1), 98-123.

LENT, R., BROWN, S. & HACKETT, G. (1994). Toward a unifying social cognitive theory of career and academic interest, choice and performance. *Journal of Vocational Behavior* 45, 79–122.

LENT, R., BROWN, S. & HACKETT, G. (2000). Contextual supports and barriers to career choice: A social cognitive analysis. *Journal of Counseling Psychology* 47, 36–49.

NATIONAL SCIENCE FOUNDATION, NATIONAL CENTER FOR SCIENCE AND ENGINEERING STATISTICS. (2015). Science and Engineering Degrees: 1966-2012. Detailed Statistical Tables NSF 15-326. Arlington. V.A. Available at https://www.nsf.gov/statistics/2015/nsf15326/#field

OCUMPAUGH, J. (2015). Baker Rodrigo Ocumpaugh monitoring protocol (BROMP) 2.0 technical and training manual. *New York, NY and Manila, Philippines: Teachers College, Columbia University and Ateneo Laboratory for the Learning Sciences*.

PARDOS, Z. A., BAKER, R. S., SAN PEDRO, M. O., GOWDA, S. M., & GOWDA, S. M. (2013, April). Affective states and state tests: Investigating how affect throughout the school year predicts end of year learning outcomes. In *Proceedings of the Third International Conference on Learning Analytics and Knowledge* (pp. 117-124). ACM.

PERIN, A. & ANDERSON, M. (2019, April 10). Share of U.S. Adults using social media including Facebook, is mostly unchaged since 2018 [Web log post]. Retrieved January 7, 2019. from https://pewrsr.ch/2VxJuJ3.

PENG, C. Y. J., LEE, K. L., & INGERSOLL, G. M. (2002). An introduction to logistic regression analysis and reporting. *The Journal of Educational Research*, *96*(1), 3-14.

PRESIDENT'S COUNCIL OF ADVISORS ON SCIENCE AND TECHNOLOGY (PCAST). (2012). *Report to the President: Engage to Excel: Producing One Million Additional College Graduates with Degrees in Science, Technology, Engineering, and Mathematics.* Available at http://www.whitehouse.gov/sites/default/files/microsites/ostp/pcast-engage-to-excel-final_2-25-12.pdf.

REINHOLD, S., HOLZBERGER, D., & SEIDEL, T. (2018). Encouraging a career in science: a research review of secondary schools' effects on students' STEM orientation. *Studies in Science Education*, *54*(1), 69-103.

RUIZ, E.C. (2012). *Research summary: Setting higher expectations: Motivating middle graders to succeed*. Retrieved December 24, 2018 from http://www.amle.org/TabId/270/ArtMID/888/ArticleID/307/Research-Summary-Setting-Higher-Expectations.aspx/

SAN PEDRO, M. O., BAKER, R., BOWERS, A., & HEFFERNAN, N. (2013, July). Predicting college enrollment from student interaction with an intelligent tutoring system in middle school. *In S. K. D'Mello, R. A. Calvo, & A. Olney (Eds.)*, *Proceedings of the 6th International Conference on Educational Data Mining* (pp 171-184).

SAN PEDRO, M. O., OCUMPAUGH, J., BAKER, R. S., & HEFFERNAN, N. T. (2014). Predicting STEM and Non-STEM College Major Enrollment from Middle School Interaction with Mathematics Educational Software. *In Proceedings of the 7th International Conference on Educational Data Mining* (pp. 276-279).

U.S. DEPARTMENT OF EDUCATION, NATIONAL CENTER FOR EDUCATION STATISTICS. (2019). *The Condition of Education 2019* (NCES 2019-144), Undergraduate Retention and Graduation Rates.

U.S. DEPARTMENT OF LABOR, BUREAU OF LABOR STATISTICS. (2014). Chapter 2: Higher Education in Science and Engineering. Available at https://www.nsf.gov/statistics/seind14/index.cfm/chapter-2/c2s2.htm

VAN TUIJL, C., & VAN DER MOLEN, J. H. W. (2016). Study choice and career development in STEM fields: an overview and integration of the research. *International Journal of Technology and Design Education*, *26*(2), 159-183.

VINCENT, K. B., KASPERSKI, S. J., CALDEIRA, K. M., GARNIER-DYKSTRA, L. M., PINCHEVSKY, G. M.,O'GRADY, K. E., & ARRIA, A. M. (2012). Maintaining superior follow-up rates in a

longitudinal study: Experiences from the College Life Study. *International journal of multiple research approaches*, *6*(1), 56-72.

WANG, X. (2013). Why students choose STEM majors: Motivation, high school learning, and postsecondary context of support. *American Educational Research Journal*, *50*(5), 1081-1121.