Exploring College Major Choice and Middle School Student Behavior, Affect and Learning: What Happens to Students Who Game the System?

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ABSTRACT
Choosing a college major is a major life decision. Interests stemming from students' ability and self-efficacy contribute to eventual college major choice. In this paper, we consider the role played by student learning, affect and engagement during middle school, using data from an educational software system used as part of regular schooling. We use predictive analytics to leverage automated assessments of student learning and engagement, investigating which of these factors are related to a chosen college major. For example, we already know that students who game the system in middle school mathematics are less likely to major in science or technology, but what majors *are* they more likely to select? Using data from 356 college students who used the ASSISTments system during their middle school years, we find significant differences in student knowledge, performance, and off-task and gaming behaviors between students who eventually choose different college majors.

Categories and Subject Descriptors
J.4 [**Social and Behavioral Sciences**]: Psychology

General Terms
Human Factors.

Keywords
College Major Choice, Affect Detection, Knowledge Modeling, Educational Data Mining, Predictive Analytics, Engagement

1. INTRODUCTION
The interests that drive a student's choice of college major are usually fostered by their early learning experiences. According to Social Cognitive Career Theory (SCCT) [7], academic and career choices are shaped throughout middle school and high school by environmental supports and barriers, where higher levels of interest emerge within contexts in which the individual has higher self-efficacy and outcome expectations; these interests lead to the development of intentions or goals for further exposure and engagement with the activity [7]. Interests formed during early stages mediate relations between high school students' self-efficacy and their college major choice. This self-efficacy, in turn, mediates the relations between high school students' ability and their formed interests. This model suggests that deepening students' ability could increase their self-efficacy in that domain, influencing their interests and choices in turn. Previous research on academic achievement, self-perception, and motivation suggests that these factors, which influence career trajectories, may emerge during middle school [7, 8]. As such, determining which middle-school behaviors are most predictive to a student's eventual college major could help us to identify factors that are still malleable, improving the opportunities available to students, particularly those who avoid certain careers which may be due to self-efficacy issues.

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In this paper, we connect fine-grained assessments of student learning, affect and behavior to the long-term outcome of college major choice, examining how these elements relate to each other. Similar connections have already been demonstrated. Not only are student learning, affect and behavior in middle school classroom associated with college enrollment [14], they are also found to be associated with a student's choice of a STEM or Non-STEM major [15]. For example, [15] showed that the disengaged behavior of gaming the system in middle school indicates that the student is less likely to enroll in a STEM major when they go to college, but not which (non-STEM) major that behavior was most associated with. In this study, we explore these relationships more precisely, showing correlations between learning and engagement within middle school use of ASSISTments and the selection of specific college major categories, across both STEM and non-STEM classifications. We conduct this study using data from 356 college students who used ASSISTments for middle school mathematics for one or more years between 2004 and 2007. We distill measures of student learning, affect and engagement, and study whether these factors are associated with specific college majors, contributing to the further elaboration of career development theory and the generation of more actionable predictions about college major.

2. METHODS

2.1 Data Source: The ASSISTments System

This study explores student outcomes from their interactions with the ASSISTments system [12]. ASSISTments *assesses* a student's knowledge while *assisting* them in learning, providing teachers with formative assessment of students as the students' progress in their acquisition of specific knowledge components. Within the system, each problem maps to one or more cognitive skills. When students working on an ASSISTments problem answer correctly, they proceed to the next problem. When they answer incorrectly (Figure 1), the system scaffolds instruction by dividing the problem into component parts, stepping students through each before returning them to the original problem (as in Figure 2). Once the correct answer to the original question is provided, the student is advanced to the next question. Teachers can assign both in-class assignments and homework with ASSISTments, which provides them with the performance data needed to track misconceptions and discuss them in class.

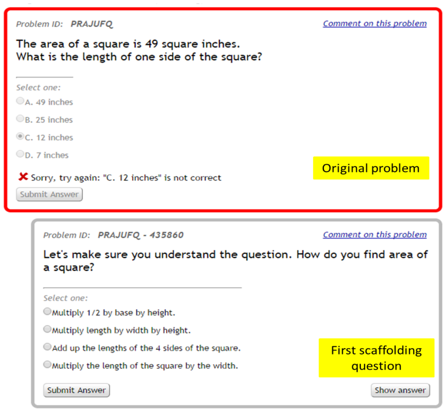

Figure 1. Example of an ASSISTments problem.

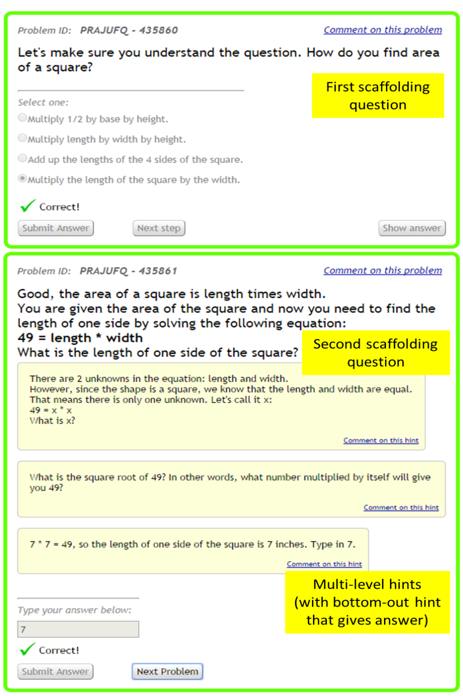

Figure 2. Example of Scaffolding and Hints in an ASSISTments Problem.

2.2 Data

2.2.1 College Major Choice Data

For this study, over 2,500 students who used ASSISTments during their middle school mathematics classes in 2004-2007 were invited to partake in a survey about their post-high school academic and career achievements. These students were drawn from three school districts in the Northeastern US. One was a low-performing district in a large, urban area, serving large proportions of students who are English language learners and/or who are eligible for free or reduced-price lunches. The other two districts are from suburban, middle-class populations.

425 students responded to this survey, which asked students to specify the degree program(s) they were enrolled in (if any), whether they were engaged in full or part-time employment, and what their current employment was. Of 425 respondents, 365 indicated that they were enrolled in a degree program. Majors were grouped into eight general classifications provided by The College Board [16], and each student in our sample was labeled accordingly: Arts & Humanities (ArtsH), Business (Busi), Health & Medicine (HealthMed), Interdisciplinary Studies (Inter), Public & Social Services (PubSoc), Science, Math & Technology (SciMathTech), Social Sciences (SocSci), and Trades & Personal Services (TrPerServ). For the purpose of comparing our middle school factors to each of these classifications, we removed one classification with only 9 students (the "Trades & Personal Services") leaving 356 students in the study.

2.2.2 Middle School Data from ASSISTments

Log files of student interactions ASSISTments were obtained for these 356 respondents, who generated a total of 311,450 actions by answering a total of 160,128 original and scaffolding problems, with an average of 450 problems per student. As discussed below, previously developed models of knowledge, affect, and behavior [9, 10] were applied to this data and used as features in our final predictive model of college major choice.

2.3 Computing Student Knowledge, Engagement, and Affect

The features evaluated for each college major group were generated using automated detectors of student engagement and learning previously developed and validated for ASSISTments. These included models of student knowledge, disengagement, and educationally-relevant affective states. Information about usage, such as the proportion of correct actions and the number of tutor actions made by the student – a proxy for overall usage were used as features as well. Each of the detectors was applied to every action in the data set for these 356 students who used the system, in the same fashion as in previous publications.

2.3.1 Student Knowledge

Corbett and Anderson's [5] Bayesian Knowledge Tracing (BKT) model, a knowledge-estimation model that has been used in a number of ITS systems, was applied to the study data set. BKT infers students' latent knowledge from their performance on problems involving the same set of skills. Each time a student attempts a problem or problem step for the first time, BKT recalculates the estimates of that student's knowledge for the skill involved in that problem, and were applied to each of the student's subsequent attempts on that problem.

2.3.2 *Affect and Disengaged Behaviors*

To obtain assessments of affect and disengagement, we leveraged existing detectors within ASSISTments [10]. Detectors of four affective states were utilized: boredom, engaged concentration, confusion and frustration. Detectors of three disengaged behaviors were also utilized: off-task, gaming, and carelessness. Due to results concerning population validity among our affect detectors [9], two sets of detectors were used. Data from students who attended urban schools were labeled using models optimized for students in urban schools [9, 10], and data from students who attended suburban schools were labeled using models optimized for students in suburban schools [9].

Except for carelessness (explained in the next section), affect and behavior detectors were developed in a two-stage process: first, student affect labels were acquired from field observations conducted using the BROMP protocol and HART Android app which time-stamps each observation (reported in [10]), and then those labels were synchronized with the log files generated by ASSISTments at the same time. This process resulted in automated detectors that can be applied to log files at scale, specifically the data set used in this project (action log files for the 356 students). Detectors were constructed using only log data from student actions within the software occurring at the same time as or before the observations. They were applied to our dataset, producing confidence values for each construct that was averaged across the log data for each student. These confidences were rescaled as in [10, 14], in order to correct for bias caused by resampling during training.

2.3.3 *Carelessness*

Carelessness is operationalized using contextual slip estimates—the probability that despite knowing the skill to answer an item, a specific incorrect action made by the student for that item is the result of slip or carelessness (see [1]). The probability of carelessness/slip is assessed contextually and is different for each student action depending on the context of the student error, which may include speed of the action, and the student's history of help-seeking from the tutor. This study uses carelessness models that were previously constructed for ASSISTments [10].

2.4 Statistical Tests and Modeling

For each of the constructs assessed through student log files, aggregate student-level predictor variables were created by taking the average of the predictor feature values for each student. Hence, a student has a single assessment for each construct. Preliminary analysis revealed that these features were generally not normally distributed in each of the college major groups. For this reason, non-parametric tests were used to analyze differences between different college major groups.

3. RESULTS

3.1 Kruskal-Wallis Test

We first examined the individual effects of each features, testing each to determine whether it appears in at least one college major group at significantly higher or lower values than are found in the other groups. We used the Kruskal-Wallis non-parametric test to evaluate the mean rank for each group. We also used the false discovery rate method to adjust the required alpha for significance and to reduce the occurrence of false positives, controlling for inflation of Type 1 error [3]. We found significant differences for gaming the system (χ^2 = 22.767, p = 0.001, adjusted α = 0.01), student knowledge (χ^2 = 21.884, p = 0.001, adjusted α = 0.015), correctness (χ^2 = 25.086, p < 0.001, adjusted α = 0.005), and carelessness (χ^2 = 16.758, p = 0.010, adjusted α = 0.02) in at least one pair of major groups. Affective states were not significantly different between major groups.

We can determine which major groups are higher and lower for these features by conducting multiple pairwise comparisons using the Mann-Whitney U test. Tables 1-4 show adjusted p-values of comparisons done between pairs of major groups.

Table 1. Multiple Comparisons for Correctness. (- significant; * - marginally significant)**

Pairwise Mean Ranks of Correctness		Mann-WhitneyU	p-value	Adjusted α
ArtsH 49.42	Busi 38.61	548.00	0.058	0.024
41.88	HealthMed 38.31	614.00	0.511	0.040
29.54	Inter 21.13	207.00	0.041	**0.021***
29.85	PubSoc 19.52	173.00	0.012	**0.014****
57.85	SciMathTech 59.97	1153.00	0.780	0.050
60.69	SocSci 52.54	905.00	0.247	0.038
Busi	HealthMed 60.75	1183.00	0.070	0.026
49.75	Inter 39.04	637.00	0.627	0.048
41.82	PubSoc 35.39	538.00	0.212	0.036
42.56	SciMathTech 83.53	1837.00	0.002	**0.005****
61.23	SocSci 74.88	1937.00	0.087	0.033
62.98				
Health 42.15	Inter 30.58	434.00	0.034	**0.019***
Med	PubSoc 28.26	374.00	0.010	**0.010***
42.31	SciMathTech 76.21	2051.00	0.156	0.031
65.94	SocSci 65.80	1993.00	0.526	0.043
70.17				
Inter 25.00	PubSoc 22.96	252.00	0.610	0.045
40.83	SciMathTech 63.11	680.00	0.004	**0.007****
43.79	SocSci 56.34	751.00	0.079	0.029
PubSoc 35.26	SciMathTech 63.68	535.00	<0.01	**0.002****
39.48	SocSci 56.79	632.00	0.016	**0.017****
SciMathTech 96.70	SocSci 77.18	2926.00	0.011	**0.012****

In Table 1, students enrolled in Interdisciplinary Studies and Public & Social Services majors show lower performance (less correctness) in middle school usage of ASSISTments, compared to students enrolled in Arts & Humanities or Health & Medicine. Additionally, Public & Social Services majors were less correct in middle school than Social Sciences majors. On the other hand, students in Science, Math & Technology majors show better performance than those who major in Business, Interdisciplinary Studies, or Public & Social Services, and Social Sciences. This complements our results for student knowledge (Table 2), where Science, Math & Technology majors showed higher knowledge than students who majored in Business, Interdisciplinary Studies or Public & Social Services.

Table 2. Multiple Comparisons for Student Knowledge. (- significant; * - marginally significant)**

Pairwise Mean Ranks of Student Knowledge		Mann-WhitneyU	p-value	Adjusted α
ArtsH 48.38	Busi 39.09	575.00	0.103	0.026
41.35	HealthMed 38.58	628.00	0.611	0.045
29.58	Inter 21.08	206.00	0.040	0.014
28.88	PubSoc 20.61	198.00	0.043	0.019
55.15	SciMathTech 60.73	1083.00	0.463	0.038
58.00	SocSci 53.39	975.00	0.513	0.040
Busi 50.98	HealthMed 59.40	1253.00	0.165	0.033
41.96	Inter 38.71	629.00	0.569	0.043

	42.07	PubSoc 36.61	566.00	0.341	0.036
	61.11	SciMathTech 83.61	1830.00	0.002	**0.005******
	63.54	SocSci 74.49	1969.00	0.115	0.029
Health	41.67	Inter 31.63	459.00	0.065	0.024
Med	41.37	PubSoc 30.39	423.00	0.044	0.021
	65.23	SciMathTech 76.61	2014.00	0.116	0.031
	68.69	SocSci 66.74	2070.00	0.777	0.050
Inter		PubSoc 23.13	256.00	0.670	0.048
24.83		SciMathTech 63.37	656.00	0.002	**0.007******
	39.83	SocSci 56.78	715.00	0.042	0.017
	42.29				
PubSoc	37.70	SciMathTech 63.08	591.00	0.001	**0.002******
	41.00	SocSci 56.37	667.00	0.032	0.010
SciMathTech					
	95.04	SocSci 79.04	3078.00	0.036	0.012

Table 3. Multiple Comparisons for Gaming the System.
(- significant; * - marginally significant)**

Pairwise Mean Ranks of Gaming the System			Mann-WhitneyU	p-value	Adjusted α
ArtsH	37.15	Busi 44.21	615.00	0.216	0.031
	37.62	HealthMed 40.44	627.00	0.603	0.046
	21.58	Inter 29.75	210.00	0.048	0.019
	19.69	PubSoc 31.00	161.00	0.006	**0.005***
	63.96	SciMathTech 58.24	1080.00	0.451	0.038
	50.69	SocSci 55.71	967.00	0.477	0.043
Busi		HealthMed 51.56	1303.00	0.278	0.033
58.14		Inter 44.42	602.00	0.396	0.036
	39.56	PubSoc 47.57	493.00	0.084	0.024
	37.65	SciMathTech 68.11	1988.00	0.013	**0.014******
	86.12	SocSci 67.89	2164.00	0.459	0.040
	73.04				
Health	35.42	Inter 45.17	464.00	0.074	0.021
Med		PubSoc 48.13	365.00	0.007	**0.010******
33.52		SciMathTech 68.41	2016.00	0.118	0.026
	79.76	SocSci 68.78	2027.00	0.632	0.048
	65.48				
Inter		PubSoc 24.91	255.00	0.655	0.050
23.13		SciMathTech 54.20	708.00	0.007	**0.007******
	75.00	SocSci 51.13	790.00	0.143	0.029
	61.58				
PubSoc	83.30	SciMathTech 51.67	476.00	<0.001	**0.002******
	68.00	SocSci 48.79	598.00	0.008	**0.012******
SciMathTech					
	79.16	SocSci 96.86	3004.50	0.036	**0.017***

Results for gaming the system (Table 3) show that students enrolled in the Public & Social Services majors are likely to exhibit this behavior at rates significantly higher than those found among students in Arts & Humanities, Health & Medicine, Social Sciences, and Science, Math & Technology. Students majoring in Business, Interdisciplinary Studies and Social Sciences (the groups whose gaming behaviors were not significantly lower than Public & Social Service majors) were significantly more likely to game than students in Science, Math & Technology.

Table 4. Multiple Comparisons for Carelessness.
(- significant; * - marginally significant)**

Pairwise Mean Ranks of Carelessness			Mann-WhitneyU	p-value	Adjusted α
ArtsH	48.23	Busi 39.16	579.00	0.112	0.029
	39.69	HealthMed 39.40	671.00	0.958	0.050
	29.15	Inter 21.54	217.00	0.065	0.010
	28.27	PubSoc 21.30	214.00	0.089	0.019
	54.65	SciMathTech	1070.00	0.413	0.036
	56.04	60.87	1026.00	0.774	0.043
		SocSci 54.01			
Busi	50.56	HealthMed 59.87	1229.00	0.125	0.031
	41.70	Inter 39.33	644.00	0.679	0.040
	41.40	PubSoc 38.26	604.00	0.584	0.038
	62.18	SciMathTech	1891.00	0.004	**0.002***
	62.98	82.95	1937.00	0.087	0.017
		SocSci 74.88			
Health	41.31	Inter 32.42	478.00	0.103	0.024
Med	40.73	PubSoc 31.83	456.00	0.103	0.021
	66.56	SciMathTech	2083.00	0.199	0.033
	68.60	75.86	2075.00	0.795	0.045
		SocSci 66.80			
Inter	24.42	PubSoc 23.57	266.00	0.831	0.048
	41.58	SciMathTech	698.00	0.006	**0.005***
	43.67	62.91	748.00	0.075	0.014
		SocSci 56.38			
PubSoc	42.39	SciMathTech	699.00	0.012	**0.007***
	49.87	61.90	733.00	0.104	0.026
		SocSci 55.56			
SciMathTech					
	93.93	SocSci 80.28	3180.00	0.074	0.012

Results for carelessness (Table 4) overlap with findings for correctness (Table 1) and knowledge (Table 2). Students enrolled in Science, Math & Technology majors showed higher carelessness during their middle school use of ASSISTments, compared to students enrolled in Business, Interdisciplinary Studies or Public & Social Services majors.

4. DISCUSSION AND CONCLUSION

In this paper, we applied fine-grained models of student knowledge, student affect (boredom, engaged concentration, confusion) and behavior (off-task, gaming, slip/carelessness) to data from 356 college students who used an educational software in mathematics over the course of a year (or more) during their middle school. Our results show that success within middle school mathematics (indicated by correct answers and high probability of knowledge in ASSISTments) is more common in students who eventually enroll in Science, Math & Technology majors than in Business, Interdisciplinary Studies, Public & Social Services, or Social Sciences majors, a finding that aligns with studies that conceptualize high achievement as a sign of STEM major readiness and enrollment in STEM programs [17].

The disengaged behavior of gaming the system during middle school mathematics is found to be associated more with students enrolled in Business, Interdisciplinary Studies, Public & Social Services, and Social Sciences, and less with students enrolled in Science, Math & Technology. This association is not yet fully understood. Previous research has shown that gaming negatively impacts learning [4], but it is also a particularly strong indicator of disengagement with mathematics, suggesting that students' lack of interest in STEM majors may manifest early. If gaming reduces the likelihood of pursuing Science, Math & Technology major because it reduces learning, remediation may be relatively easy. Gaming's effects on learning can be successfully remediated through alternate opportunities to learn the bypassed material [2]. However, if gaming is instead an early indicator of lack of interest in pursuing a Science, Math & Technology major, remediation may be more difficult, but perhaps not necessary. (The world needs people in a range of professions, though one hopes that these gaming behaviors will not convey to other domains, as they are just as problematic in business or the social sciences as in STEM careers [cf. 13].)

These relationships between middle school student behavior and learning with eventual college major selection complement current understandings of why students who choose to enroll in a particular major. Holland's theory [6] asserts that students make academic and career choices compatible with their personality and driven by their preferred activities, interests and competencies [6, 11]. Business majors are often oriented toward attaining goals through leadership or manipulation (enterprising) and enjoy systematic ways of performing activities (conventional). Those who are inclined towards interpersonal and social environments (social) are likely to choose majors in the Social Sciences or Public & Social Services. Students who prefer creative endeavors related to unstructured activities (artistic) find a fit in Liberal Arts or Interdisciplinary Studies. Finally, students who enroll in Science, Math & Technology majors are known to prefer practical and concrete activities (realistic) that involve knowledge acquisition and problem solving (investigative), a claim supported by our findings that success with ASSISTments is most likely among Science, Math & Technology majors.

One curious finding in our study is that affective states are not strongly predictive of college major choice. This is surprising given that affect *is* predictive of whether students go to college [14], but perhaps it is less relevant to domain-specific choices. A possible explanation is that student affect may be less relevant for college major choice than how students respond to that affect (e.g., whether or not boredom triggers disengaged behaviors that reduce learning), a hypothesis that is supported by our current results. It is also possible that social conditions (e.g., parental or school support) provide more varied learning opportunities for the college-bound cohort (which could, in turn, impact interest), so that we might be better considering affective patterns among the college-bound cohort once they get a bit older. Either way, the lack of relationship between affect and college major does not suggest that negative affect during middle school should not be attended to, as it still impacts both learning outcomes and college attendance [10, 14].

The goal of this paper, however, is not a final prediction, but rather an opportunity to understand whether student behavior is related to long-term outcomes (college major selection), providing an opportunity for educators to provide informed guidance that helps to grow, harness, and sustain student interests, as early as middle school.

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