Exploring Selective College Attendance and Middle School Cognitive and Non-Cognitive Factors within Computer-Based Math Learning

Maria Ofelia Z. San Pedro, ACT, Inc.
Ryan S. Baker, University of Pennsylvania
Alex J. Bowers, Teachers College, Columbia University
Neil T. Heffernan, Worcester Polytechnic Institute

Abstract

Middle school is a key juncture in the processes that influence whether a student will have a successful post-secondary outcome such as going to a selective college, but research on factors leading to this choice does not yet utilize the extensive fine-grained data now becoming available on middle school learning and engagement. Leveraging recent methodological advances in measurement and educational data mining, we apply automated detectors which can infer student learning, academic emotions, and engagement, to data from middle school mathematics software usage. We then use the measures derived to predict which students will go to selective colleges several years later. The result is a model that can distinguish whether a student will eventually go to either a selective or a non-selective college 77.4% of the time. The resulting model can also run in real-time, creating the potential for providing actionable data quickly to teachers and guidance counselors.

Key Words: Selective College, Post-Secondary Institution, Engagement, Affect, Academic Emotions, Intelligent Tutoring System

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Attending a more selective post-secondary institution has been shown to be associated with higher-quality learning, higher likelihood to graduate, and improved career prospects and economic gains (Bowen, Chingos, & McPherson 2009; Carnevale & Rose, 2003; Ovink, Kalogrides, Nanney, & Delaney, 2018; Shamsuddin, 2016; Thomas, 2000). Schools that are more selective tend to have higher access to financial resources, more faculty attention that can increase a student's success in college, more career counseling, better access to internships, and better preparation for application to graduate schools (Carnevale & Rose, 2003; Hoxby, 2009). However, access to selective colleges is skewed by race, ethnicity and socioeconomic status. Overall, white and Asian students are found to be more likely to enroll in four-year colleges, especially in highly selective colleges (Goldrick-Rab, 2007; Reardon, Baker, & Klasik, 2012), while African- American and Hispanic students are less represented in highly selective colleges (Carnevale & Rose, 2003; Reardon, Baker, & Klasik, 2012). Students from low SES families usually lack the economic resources necessary to pursue postsecondary education (Ellwood & Kane, 2000; Karabel & Astin, 1975; Zhou & Bower, 2020). While demographics appear to be a significant part of the gaps in access to a selective college, they do not illuminate all the possible reasons why students fail to attend college, let alone a selective college. In particular, some students may not attend a selective college due to experiences that occur much early on in their lives. Many students effectively drop out of the pipeline towards academic success well before reaching college (Balfanz, 2009; Balfanz, Herzog, & Mac Iver, 2007; Bowers, 2010, Bowers & Sprott, 2012a; Bowers & Sprott, 2012b; Bowers & Zhou, 2019; Neild, 2009). Such change occurs both in terms of decreasing motivation (Anderman & Maehr, 1994) or greater degree of academic failure that can begin to manifest in middle school (NMSA, 2002; Neild, 2009). This often results in extreme forms of disengaged behavior such as non-attendance and classroom misconduct (Tobin & Sugai, 1999; Tobin, Sugai, & Colvin, 1996).

Social Cognitive Career Theory and Pathway to College

Due to the possibility of this kind of early school disengagement, school counselors are encouraged to support students in developing the cognitive and non-cognitive skills necessary to being college-ready (Conley, 2008; Conley, Lombardi, Seburn, & McGaughy, 2009), and help them transition to postsecondary education (Gibbons et al., 2006). If students who are at risk could be spotted early, better-targeted interventions could be developed for these students (Bowers, 2010; Bowers, In Press). Several of these potential actionable factors are seen in Social Cognitive Career Theory (SCCT, Lent, Brown, & Hackett, 1994; Lent, Brown, & Hackett, 2000). According to SCCT, higher levels of interest in an activity emerge within contexts where the individual has higher self-efficacy and outcome expectations, leading to the development of intentions or goals for further exposure and engagement with that activity (Lent, Brown, & Hackett, 1994).

<Figure 1 goes here>

Recent SCCT research has focused on high school or college students, and relatively few studies have analyzed hypotheses related to SCCT in middle school students (but see Fouad & Smith, 1996; Gibbons & Borders, 2010; Turner & Lapan, 2002). However, it is in middle school where students start to develop their abilities and interest in pursuing their studies and advanced careers (Cabrera, La Nasa, & Burkum, 2001; Camblin, 2003). During middle school, students begin to develop academic abilities, interests, and choices that will have a strong influence on later academic outcomes (Cupani & Pautassi, 2013), and become engaged or disengaged from school and learning, driven in part by changes in self-perception such as whether they see themselves as intelligent and capable of succeeding academically (Camblin, 2003; NMSA, 2002).

Hence, there have been increasing recommendations that college planning begin as early as sixth grade (Allensworth, Gwynne, Moore, & De la Torre, 2014). Students who start thinking about college as early as middle school tend to become interested in achieving a good academic record. They may plan to take appropriate courses once they are in high school or choose to be involved in extracurricular activities that will contribute to their college applications (Roderick, Coca, & Nagaoka, 2011; Roderick, Nagaoka, Coca, & Moeller, 2008).

Cognitive and Non-cognitive Factors in Academic Settings

Understanding students' long-term outcomes such as selective college attendance necessitates looking beyond their academic performance and individual abilities, towards "non-cognitive factors" (Farrington et al., 2012) in their learning experiences such as academic emotions and engaged or disengaged behaviors . One example of an academic emotion is *boredom*, common in many middle school classrooms (e.g. Rowe, McQuiggan, Robison, & Lester, 2009; Pardos et al., 2013). A second affective state, *engaged concentration*, is related to Csikszentmihalyi's construct of flow (1990) and describes when a student experiences intense concentration, focused attention, and complete involvement in their task (Baker, D'Mello, Rodrigo, & Graesser, 2010). Another common academic emotion is *confusion*, where a student is uncertain how to complete a task due to a mismatch between their prior knowledge and incoming information, creating cognitive disequilibrium (D'Mello, Lehman, Pekrun, & Graesser, 2014; Rozin & Cohen, 2003). Students can also experience *frustration* (Kort, Reilly, & Picard, 2001), where students have feelings of distress when they encounter tasks that may be too difficult for their skills (Csikszentmihalyi, 1990).

Negative academic emotions can lead students to zone out (Drummond & Litman, 2010; Feng, D'Mello, & Graesser, 2013) or exhibit disengagement in classrooms. *Gaming the system* is a behavior when a student exploits the properties of a learning activity (i.e., within an educational software) to obtain the solution instead of through meaningful learning (Baker, Corbett, Koedinger, & Wagner, 2004). In *off-task behavior*, the student engages in extraneous activities and completely disengages from their learning tasks. In learning activities, students also exhibit *careless behavior* when they make errors on questions despite knowing how to successfully answer (Clements, 1982).

These disengaged behaviors, together with boredom, have been found to be associated with poorer learning, lower self-efficacy (Narciss, 2004; Schunk, 1989), diminished interest in educational activities, negative attitudes toward math content (Baker, 2007; Baker et al., 2008), poorer performance on standardized examinations (Pardos et al., 2013), and, most importantly, increased attrition and dropout rates (Craig, et al., 2004; Daniels et al., 2009; Goodman, 1990; Mann & Robinson, 2009; Pekrun et al., 2010). By contrast, students who are more engaged in school tend to have higher academic motivation and achievement (Fredericks, Blumenfeld, & Paris, 2004; Pardos et al., 2013). Academic emotions and disengaged behaviors are also associated with college enrollment (San Pedro et al., 2013); students who frequently experience engaged concentration in middle school mathematics are more likely to go to college, while students who frequently experience confusion and boredom or who game the system are less likely to go to college (San Pedro et al., 2013). Hence, engagement and academic emotions in middle school learning appear to play an essential early role in students' educational experiences.

Educational Technology in Assessing Cognitive and Non-Cognitive Factors

Researchers in recent years have used educational technologies to study academic emotions and engagement, both in laboratory settings and in actual classrooms, in fine-grained detail. Educational data mining (EDM; Baker & Yacef, 2009) researchers have developed automated models (using a combination of interaction data and classroom observations of students) that can infer students' academic emotions, engagement, and knowledge in real time, and have found evidence that the constructs these models infer are associated with differences in student outcomes. These recent advances have progressed in large measure due to the expansion of computer-based learning environments usage in schools, providing a rich source of data that helps us understand students' learning processes (Canfield, 2001; Heffernan & Heffernan, 2014; Koedinger & Corbett, 2006). .

Assessments or measures derived from these models are different from the questionnaire responses and coarse-grained variables (such as demographic information or test scores) typically used in research on educational outcomes. Assessments developed using EDM predict educational outcomes such as learning gains (Baker, Corbett, Koedinger, & Wagner, 2004; Cocea, Hershkovitz, & Baker, 2009; Sabourin, Mott, & Lester, 2011) and standardized exams (Pardos et al., 2013), and have been widely used within online learning environments that produce rich student interaction data, such as intelligent tutoring systems (Baker, D'Mello, Rodrigo, & Graesser, 2010; Pardos et al., 2013; Walonoski & Heffernan, 2006) and educational games (Shute, Moore, & Wang, 2015; Bosch et al., 2015)..

Despite these advances, there has been limited research on whether these fine-grained measures can predict long-term student outcomes – in particular, attending a selective college. In this paper, we evaluate and predict whether a student will attend a selective college or not, five to six years later, based on their interaction with an educational software system, the ASSISTments system, during middle school. We assess key aspects of student emotion, engagement, and knowledge by leveraging existing machine-learned detectors of student affect, knowledge, and engaged/disengaged behaviors previously developed for the ASSISTments system. We investigate in particular, the following research questions:

1) How are middle school student knowledge, academic emotions, and disengaged behaviors associated with going to a selective college?
2) Are middle school student knowledge, academic emotions, and disengaged behaviors predictive of going to a selective college?

We conclude with a discussion of potential implications for the design and interventions of interactive educational systems for sustained attendance and engagement in school.

Methods

We investigate student knowledge, performance, affect and engagement through students' interaction with the ASSISTments system (Heffernan & Heffernan, 2014) when they were in their middle school years (7th or 8th grade). We conduct this research in a data set of 5,472 students who used the ASSISTments system, between 2004 and 2008. Enrollment records in a post-secondary institution for the 5,742 students were obtained in 2013 from the National

Student Clearinghouse (http://www.studentclearinghouse.org). For purposes of focusing on college selectivity, students not found to be enrolled in a post-secondary institution were excluded from our sample. Out of the 5,742 students, 2,810 students enrolled in a post-secondary institution and were considered in the current study. Also, for the purposes of the analyses in the present study, we only considered the last post-secondary institution the student enrolled in, using this as basis for assessing whether the student attended a selective college.

The ASSISTments System

The ASSISTments system (Figure 1) (Heffernan & Heffernan, 2014) is a tutoring system for middle school mathematics provided by Worcester Polytechnic Institute (WPI) which serves as the data source for our independent variables. This free web-based educational system delivers mathematics problems and questions, assesses student performance, provides hints and suggestions, provides targeted feedback on common errors, and scaffolds the development of improved answers by breaking complex problems into simpler steps. When students working on an ASSISTments problem answer correctly, they proceed to the next problem. If they answer incorrectly, they are provided with scaffolding questions where the problem is broken down into its component steps in order to concretize the systematic thinking needed to solve the problem. The intention is to identify which part of the student's thinking is incorrect. This information about the student's problem solving is then provided to teachers as detailed reports and summaries for assessment and diagnostic purposes.

<Figure 2 goes here>

Interaction log data from the ASSISTments system were obtained for the sample population of 2,810 students from middle schools in the Northeastern United States. The students used the system at various times starting from school years 2004-2005 to 2007-2008 (with a few students continuing tutor usage until 2008-2009). These students were drawn from four districts that used the ASSISTments system at various times throughout the course of the year. Two districts were urban with large proportions of students requiring free or reduced-price lunches due to poverty, relatively low scores on state standardized examinations, and large proportions of students learning English as a second language. The other two districts were suburban, serving generally middle-class populations, with relatively higher scores on state standardized examinations. In general, students in our sample used ASSISTments three to four times a month in classes held in their school's computer lab. Students were guided and instructed by teachers trained in formative assessment. These teachers used ASSISTments in their math curricula for review of concepts and test preparation. Overall, the students in the sample made 2,024,893 actions within the software (where an action consisted of making an answer or requesting help), within 1,021,272 mathematics problems (counting both original and scaffolding problems).

Dependent Variable: College Selectivity

College selectivity measures are generally determined by an aggregate index computed across several factors, including: the median SAT or median composite ACT entrance exam score; the average high school class rank of the student; the average student GPA in high school; and the percentage of students accepted (Carnevale and Rose, 2003). Each of the 270 post-secondary institutions attended by our sample of students was classified in terms of selectivity. The most commonly-used measure of college selectivity (c.f., Carnevale & Rose, 2003; Griffith

& Rothstein, 2009; Schmidt, Burroughs, Cogna, & Houang, 2011) is the annual Barron's index (College Division of Barron's Education Series, 2012), which classifies colleges into ten categories from most selective or 'Most Competitive' to 'Noncompetitive' and 'Special', which consists of specialty institutions such as schools of music, culinary schools, automotive training schools, and art schools.

Of the 2,810 students, 32 students attended an institution with a 'Special' classification and 46 students attended an institution unclassified in Barron's. We excluded these students from our sample, leaving us with data from 2,732 students with 9 selectivity classifications to use for our analyses.

<Table 1 goes here>

Barron's index makes fine distinctions between degrees of selectivity, as shown in Table 1. In this paper, we analyze enrollment in either a selective college or a non-selective college, in a binary fashion, rather than attempting to treat this scale as numerical.

As seen in Table 1, our sample (like the national population of students) is skewed towards the 'Non-Competitive' end of the scale; our sample also has relatively few students attending universities in 'Very Competitive+' and 'Competitive+' classifications. Simplifying our DV can make it more evenly distributed and reflect more meaningful and practical distinctions between a selective school and a not selective school. We examined four different ways to split into selective/non-selective (see Table 2): 4+.vs.3-, 6+.vs.5-, 8+.vs.7-, 10+.vs.9-. We used these binary splits to label post-secondary institutions as selective or non-selective and used the resultant variable as the predicted variable in the analysis below. Figure 3 shows the number of students in each binary split for each cut-off. For the 4/3 cut-off, there are more students who went to a selective college (n = 1,540 students) than not (n = 1,192 students). For the 6/5 cut-off, 690 students went to a selective college compare to the 2,042 students went to a not selective college. For the 8/7 cut-off, there were only 339 students who went to a selective college, and in the 10/9 cut-off, only 122 students went to a selective college.

<Table 2 goes here>

<Figure 3 goes here>

Independent Variables: Student Knowledge, Academic Emotions and Behavior from Interaction Data

We predict and analyze college selectivity using a range of variables or features computed from the log files of ASSISTments. Measures of student affect (boredom, engaged concentration, confusion, frustration), student disengaged behaviors (off-task, gaming the system, carelessness), and student knowledge were derived from models. Information on student usage (the proportion of correct actions and the number of first attempts on problems made by the student, a proxy for overall usage) was directly extracted from the logs.

Figure 4 shows how models of our independent variables were developed for ASSISTments and subsequently computed from the ASSISTments interaction log data. The models of academic emotions and behavior were first reported in (Pardos et al., 2013; Ocumpaugh et al., 2014). These models were applied to every student action within the system, producing a sequence of predictions of the students' knowledge, academic emotions and behavior across the history of each student's use of ASSISTments. These could then be aggregated into a set of single overall assessments for each student.

Once the models of academic emotions, behavior and knowledge are applied to the dataset of our sample students, producing values for these independent variables, they were then used for our final model of college selectivity. This process is sometimes referred to as "discovery with models" (e.g. Baker & Yacef, 2009) where existing models are used as a component in a new and different analysis or model.

<Figure 4 goes here>

Modeling Student Knowledge.

Student knowledge was derived from tutor usage in ASSISTments by applying Corbett and Anderson's (Corbett & Anderson, 1995) Bayesian Knowledge Tracing (BKT) model to the data (Figure 5). BKT is a knowledge-estimation model which is used in many online learning systems. BKT and infers students' latent knowledge from their performance on problems. In the case of student interaction with ASSISTments, student knowledge is assessed from each student's first attempt to answer each problem. Each time a student attempts a problem or problem step for the first time, BKT calculates (and recalculates on next problem) the estimates of that student's knowledge for the skill involved in that problem or problem step. Knowledge estimations for each skill are made using four parameters: (1) L_0, the initial probability that the student knows the skill, (2) T, the probability of learning the skill at each opportunity to use that skill, (3) G, the probability that the student will give the correct answer despite not knowing the skill, and (S) the probability that the student will give an incorrect answer despite knowing the skill. Brute-force grid search was used to fit the model to the data (see Baker et al., 2010).

<Figure 5 goes here>

Modeling Academic Emotions and Disengaged Behavior.

The academic emotions modeled within ASSISTments consist of boredom, confusion, frustration, and engaged concentration. Disengaged behaviors modeled include gaming the system, off-task behavior, and carelessness. With our student sample belonging to urban and suburban districts, two sets of detectors were used: models optimized for students in urban schools were used to label data from students who attended urban schools (Pardos et al., 2013), and models optimized for students in suburban schools were used to label data from students who attended suburban schools (Ocumpaugh et al., 2014). This choice is based on evidence that urban and suburban students manifest their emotions differently in online learning (Ocumpaugh et al., 2014). The same detectors were used for gaming the system and for off-task behavior, across contexts, as these constructs manifest more consistently across populations.

These detectors were initially developed (in Pardos et al., 2013; Ocumpaugh et al., 2014) using a three-stage process: first, field observers noted down student engagement and academic emotions while students used ASSISTments using the BROMP protocol for quantitative field observation of emotion and engagement (Baker, Ocumpaugh, & Andres, 2020) and the HART field observation app for Android (Ocumpaugh et al., 2015); second, those field notes were synchronized with the log files generated by student interaction with ASSISTments at a precision of around 1-2 second error, using an internet time server; and third, data mining was used to create models that could predict the field observations (i.e. student academic emotions and engagement) from the log files. This process resulted in automated detectors of academic emotions and engagement that can be applied to log files at scale, specifically different log data from the same learning environment, such as the data set used in this project. These detectors were validated by repeatedly building them on a subset of the available data (4/5 of 229 urban students; 4/5 of 243 suburban students), and testing them on unseen students (the other 1/5), and their goodness was measured using standard metrics.

Each of the models of academic emotions and behaviors used combinations of features engineered from raw information about a student's interaction (e.g. action is a hint, first attempt at a problem is a help request, etc.) to make predictions of that emotion or behavior, discussed below. Common classification algorithms and feature selection were used in modeling each independent variable of academic emotions and behavior, choosing the model with the best performance (AUC ROC– Hanley & McNeil, 1982). These algorithms included J48 decision trees, logistic regression JRip, Naïve Bayes, REP-Trees, and K-Star (Witten & Frank, 2005)..

The effectiveness of these models of academic emotions and behaviors is shown in Table 3. The detectors achieved an average AUC ROC of 0.702, where AUC ROC indicates the probability of distinguishing a single positive example from a single negative example. An AUC ROC value of 0.5 indicates chance-level performance, and 1.0 indicates the model performs perfectly. For example, the gaming detector had an AUC ROC of 0.802; as such, it could distinguish a gaming student from a non-gaming student 80.2% of the time.

<Table 3 goes here>

Compared to gaming the system and off-task behavior and academic emotions, assessment of the disengaged behavior carelessness was generated differently. Instead of using models trained from field observations, the instance of carelessness was assessed with a model that infers whether a student error for each student action are due to not knowing the skill or due to being careless (i.e., careless errors or "slips", answering incorrectly despite actually knowing how to answer it correctly) (Baker, Corbett, & Aleven, 2008; San Pedro et al., 2011).

Modeling carelessness or slip in the context of educational software is derived from BKT where we use the "contextual slip" model from (Baker, Corbett, & Aleven, 2008; San Pedro et al., 2011) in operationalizing carelessness. To model carelessness, we apply BKT to our data to generate initial estimations of whether the student knew the skill at each problem step. Bayesian equations are then used with these estimations to compute the probability that incorrect actions were slips, based on the correctness or student performance on succeeding attempts to use the skill (Baker, Corbett, & Aleven, 2008; San Pedro et al., 2011). These probability values are then used to create a model that can predict slip or carelessness contextually at each practice opportunity, from data such as response time, past history, and the pattern and type of errors, without any future information.

Modeling College Selectivity.

We applied the detectors to measure student knowledge, academic emotions (boredom, confusion, engaged concentration, frustration), behavior (off-task behavior, gaming the system, carelessness), as well as obtaining measures of overall student correctness (a proxy for short-term academic success), and the number of actions made by the student, a proxy for overall usage (see Table 4). We then fit a logistic regression model predicting whether a student in the data set attended a selective or non-selective college, using the student average for each of the predictor values across the year (i.e., average boredom per student).

<Table 4 goes here>

We used logistic regression analysis since we have (a set of) dichotomous outcomes resulting in a non-linear relationship between our predictors and outcome variable. Choosing logistic regression allows for relatively good interpretability, while matching the statistical approach used in much of the other work predicting enrollment and success in higher education and educational pathways (Cabrera, 1994; Eccles, Vida, & Barber, 2004; Nunez & Bowers, 2011; Stephan & Rosenbaum, 2012; San Pedro et al., 2013).

The final model created for each cut-off was cross-validated at the student level (6-fold), e.g. the models were repeatedly trained on 5/6 of the students and then tested on the remaining 1/6 of the students. This procedure estimates how well the models can be expected to perform when applied to entirely new students. The model's quality was assessed using two metrics, AUC ROC (described above) and Cohen's Kappa (see Table 8). Cohen's Kappa assesses the degree to which a model is better than chance at predicting a particular category (Cohen, 1960), and is a common metric for assessing categorical predictions. Cox & Snell (1989) and the Nagelkerke's (1991) pseudo-R^2 are also used to evaluate how useful the explanatory variables are in predicting the response, quantifying the amount of variance explained by the models, following recommendations in (Bowers & Lee, 2013).

All predictor variables were standardized (using z-scores), in order to increase interpretability of the resulting odds ratios and to show a clear indication of each predictor's contribution to the class variable (college is selective).

Results

Correlational Analyses

Before developing our college selectivity model, we looked at our original, non-standardized predictors or independent variables and examined their relationships with each other. From Table 5, the strongest positive associations were found between student knowledge and carelessness ($r = 0.956$, $p < 0.001$), student knowledge and correctness ($r = 0.807$, $p < 0.001$), and confusion and boredom ($r = 0.710$, $p < 0.001$).The strongest negative associations were between correctness and gaming ($r = -0.586$, $p < 0.001$), off-task and gaming ($r = -0.503$, $p < 0.001$), and confusion and carelessness ($r = -0.500$, $p < 0.001$). Significant correlations among the predictors were evident, an indication of the existence of collinearity in a full-featured model (all predictors included in the model) for predicting whether a student will go to a selective college. Hence, we present reduced models below, rather than combining all features in a single model.

<Table 5 goes here>

We also computed the correlations between each of our predictors and the dependent variable, whether the student attended a selective college. From Table 6, selectivity or students going to a selective college, across all cut-offs, is significantly correlated to each of our predictors except for number of actions, engaged concentration in the first cut-off, and off-task behavior in the second and fourth cut-offs. We conduct this analysis across all cut-offs in order to establish that the findings are stable for different cut-offs.

For the most part, going to a selective college is positively associated with engaged concentration, student knowledge, carelessness, and correctness, while negatively associated with boredom, confusion, frustration and gaming. Surprisingly, the first and third cut-offs resulted in a weak but significant positive correlation between going to a selective college and off-task behavior.

<Table 6 goes here>

Differences of Predictors between Going to a Selective College and Not Going to a Selective College

After analyzing the correlations from Table 6, we can look at the difference in mean values for each independent variable for students who attended selective colleges and students who attended a non-selective college in each cut-off. With the exception of number of actions and off-task for two cut-offs behavior, a statistically significant difference in means for each independent variable was found between the two groups for all cut-offs (Table 7). .

<Table 7 goes here>

For all cut-offs, engaged concentration, student knowledge, percentage of correct answers, and carelessness had higher mean values for *students who attended selective colleges*. The difference in engaged concentration accords with studies relating this affective state to effective learning (Craig, Graesser, Sullins, & Gholson, 2004; D'Mello, Craig, Witherspoon, McDaniel, & Graesser, 2008; Rodrigo et al., 2009), as well as to evidence that engaged concentration with academic subjects is related to interest (Csikszentmihalyi & Schneider, 2000). In terms of student performance and learning, the differences in student knowledge and correctness indicate that successful demonstration of skill in ASSISTments during middle school is more common in students who attended a selective college. Looking at carelessness by itself, there was more carelessness for students who went to a selective college. It may seem counter-intuitive that a disengaged, careless student is more likely to go to a good college, but this finding aligns with past research that not only found carelessness to be positively associated with college enrollment (San Pedro et al., 2013), but was also more common in successful, confident students (Clements, 1982). Carelessness may be a result of overconfidence, and thus as a disengaged behavior of generally successful students.

On the other hand, boredom, confusion, frustration, and gaming the system had higher mean values for those who did *not attend a selective college*, for all cut-offs. These differences can be attributed to the fact that when boredom, confusion and frustration are not addressed properly, they may have negative influences in student learning. This is in line with previous findings that associate boredom with poorer learning outcomes (Craig, Graesser, Sullins, & Gholson, 2004; Pekrun, Goetz, Daniels, Stupnisky, & Perry, 2010; Pardos et al., 2013) and high school dropout (Farrell, 1988; National Research Council & Institute of Medicine, 2004; Rumberger, 1987). While confusion can sometimes lead to learning, when confusion is not addressed it is known to be associated with poorer learning (D'Mello & Graesser, 2012). Students who experience frustration and remain in that affective state are less likely to learn (D'Mello, Craig, Witherspoon, McDaniel, & Graesser, 2008), and can even become bored (D'Mello & Graesser, 2012). It is also not surprising that gaming the system was more frequent among students who attended a non-selective college, since gaming the system is known to be associated with poorer learning (Cocea, Hershkovitz, & Baker, 2009; Fancsali, 2015), poorer performance on standardized state exams (Pardos et al., 2013), and a lower chance of attending college (San Pedro et al., 2013).

Logistic Regression Model of Going to a Selective College

After looking at our individual variables and their relation to selective college attendance, we then built a logistic regression model that integrates multiple features and is predictive of selective college attendance. Goodness of fit metrics are given in Table 8.

<Table 8 goes here>

Our final models achieved a cross-validated AUC ROC across cut-offs ranging from 0.774 to 0.821 and cross-validated Kappa values from 0.029 to 0.419 (we discuss the low Kappa below). All the models across cut-offs were statistically significantly better than a null model, and achieved a fit of R^2 (Cox & Snell) ranging from 0.063 to 0.221 and R^2 (Nagelkerke) values from 0.204 to 0.313. These values indicate that for example in cut-off 1, the final model's predictors explain 22.1% to 29.6% of the variance of those who attended a selective college.

<Table 9 goes here>

As can be seen in Table 9, engaged concentration, confusion, frustration, gaming, student knowledge and correctness maintained the same directionality as in Tables 6 and 7 as predictors in a final model, while off-task and boredom switched direction in the overall model. Despite not having a significant correlation to attending a selective college by itself, number of actions became a significant predictor of going to a selective college when controlling for other predictors.

For the first cut-off, the final model of going to a selective college (χ^2(df = 7, N = 2732) = 680.752, p < 0.001) included engaged concentration, confusion, frustration, gaming, carelessness, correctness and number of actions as predictors. Controlling for other predictors, each unit increase in correctness increased the odds of a student going to a selective college by 2.2. Similarly, the more engaged concentration, carelessness, or usage of ASSISTments a student showed, the greater the likelihood of that student going to a selective college. On the other hand, when controlling for other predictors, the more a student exhibits confusion, frustration and gaming, the odds of the student going to a selective college reduces.

The final model for the second cut-off had engaged concentration, frustration, off-task behavior, gaming, student knowledge, correctness and number of actions for its predictors (χ^2(df = 7, N = 2732) = 650.892, p < 0.001). It is interesting to note that the resulting set of significant predictors and their relations to going to a selective college was similar to the final model in the first cut-off, with the exception of confusion being replaced by off-task behavior. When controlling for other predictors, off-task behavior is negatively associated with going to a selective college (different than its non-significant relation when considered alone), aligning with prior studies that find off-task behavior to be associated with poorer learning outcomes (Goodman, 1990; Cocea, Hershkovitz, & Baker, 2009).

The third cut-off resulted in a final model (χ^2(df = 6, N = 2732) = 353.994, p < 0.001) that had boredom, engaged concentration, frustration, student knowledge, correctness, and number of actions as predictors. Changes in a student's engaged concentration, frustration, student knowledge, correctness, or number of actions had a similar effect on the likelihood of the student going to a selective college when controlling for other predictors as for the other cut-offs. . However, in this model, once we control for other variables in the model, boredom is significant positively associated with college attendance. It is possible that once we control for students who are both bored and unsuccessful, all that remains are students who are bored with the material because it is too easy (cf. Pekrun, Goetz, Daniels, Stupnisky, & Perry, 2010).

The fourth cut-off resulted in a final model with two predictors – engaged concentration and correctness (χ^2(df = 2, N = 2732) = 176.375, p < 0.001), each of them positively associated with going to a selective college when controlling for the other predictor.

Comparing the final models of going to a selective college in the different cut-offs the model for the first cut-off performed well overall (across the R^2 values, Kappa and AUC ROC), while the model for the fourth cut-off performed the worst in terms of R^2 values and Kappa (but performed best in terms of AUC ROC). These values may be attributed to the extreme data imbalance in the fourth cut-off, where only 122 students were labeled as attending a selective college out of 2732 students. Based on its performance, we choose the final model from the first cut-off for discussion below.

Discussion and Conclusion

In this paper, we investigated a set of malleable and actionable factors that occur during a student's learning experience, outside grades, tests and demographic information: student knowledge, performance, academic emotions and behavior within a middle school learning environment. Taking data from 2,732 students who used ASSISTments over the course of a year or more in middle school, we used a combination of features of student success and engagement while using the system to develop a logistic regression model that can distinguish whether a student will eventually enroll in a selective college in four different instances (i.e. cut-offs in labeling selective and not selective colleges).

Our best-performing model (using cut-off 1) can distinguish 77.4% of the time whether a student will eventually enroll in a selective college, with engaged concentration, confusion, frustration, gaming the system, carelessness, correctness and number of actions to be significant predictors of going to a selective college. The positive connection between academic performance and attending a selective college is consistent with past research using other indicators of academic performance (cf. Baron & Norman, 1992; Carnevale & Rose, 2003; Griffith & Rothstein, 2009), studies that identify college readiness to be linked to high performance during schooling (Roderick, Nagaoka, & Coca, 2009), as well as studies that predict that college enrollment is correlated with indicators of aptitude (Christensen, Melder, & Weisbrod, 1975; Eccles, Vida, & Barber, 2004).

This final model also sheds light on the impact of emotional and behavioral factors experienced by students in classrooms. As our results here show, academic emotions and disengagement are associated with a student's choice of whether to attend a selective college or not, even after controlling for student performance and learning. Hence, affect and engagement or disengagement with school appear to be another key factor influencing these processes. Affect and engagement develop early in schooling and become particularly prominent during the middle school years. When compared to student behaviors such as school violence, fighting in class, or disrupting class (Kellam, Ling, Meriska, Brown, & Ialongo, 1998; Reinke & Herman, 2002), the academic emotions and disengaged behaviors explored in this study are very mild in nature. Nonetheless, they are associated with long-term student outcomes. While researchers have studied disengaged behavior of an intensity that leads to disciplinary referrals, the behaviors studied in this paper are more frequent, and likely more actionable than the highly problematic behaviors which result in disciplinary referrals.

Academic emotions and student behavior are likely to play an important role inthe development of academic and career self-efficacy and interests, and can thus serve as additional information and predictors in current models for college and career pathways. This richer information can also be included in reports (in software dashboards or evaluation assessments) that may assist educators in identifying at-risk students and encourage those students to participate in educational activities and programs tailored to their specific learning needs, and help them remain in the academic pipeline. In career guidance counseling studies, questionnaire-based measures are currently used to evaluate a student's career choice (cf. Betz, Borgen, & Harmon, 1996; Campbell, Hyne, & Nilsen, 1992) and attitudes toward career domains (Tapia & Marsh, 2004). As established in this study, online learning environments create a valuable opportunity to keep students from dropping out of the academic pipeline. In assessing students' learning experiences as early as middle school—through academic emotions, engaged and disengaged behavior—there is a potential for more effective interventions based on rich and meaningful information.

There have been growing efforts to develop software that automatically provides support when students are disengaged or experiencing negative affect while interacting with the software (D'Mello, Picard, & Graesser, 2007; Forbes-Riley & Litman, 2011; Rowe, McQuiggan, Robison, & Lester, 2009; Woolf et al., 2010). Results presented in this paper provide supporting evidence for which academic emotions and disengaged behaviors need to be addressed or promoted in middle school, to support long-term student achievement. For example, confused students can be given learning support to help resolve their confusion – resolved confusion is associated with better learning outcomes than never being confused at all (D'Mello & Graesser, 2012; Lee, Rodrigo, Baker, Sugay, & Coronel, 2011). Students with prolonged confusion can also transition to become bored or frustrated, another reason to address this academic emotion. Frustrated students can be provided with hints that aid in student learning or with motivational comments (D'Mello & Graesser, 2012; DeFalco et al., 2018). Students who game the system can be given supplementary materials that help them learn skills bypassed through gaming (Baker et al., 2006).

While boredom and off-task behavior did not enter into this final model, it does not mean that they cannot and should not be addressed, since they are still predictive of going to a selective college on their own. Bored students can be provided with problems that are more interesting, with greater novelty and challenge to reduce boredom or to support their emotional self-regulation (Acee et al., 2010; Pekrun, Goetz, Daniels, Stupnisky, & Perry, 2010). Similarly, it may be worth exploring the addition of data on engagement and affect to formative assessment systems used by teachers, for example when students encounter frustration when completing their homework. These indicators, can inform educators as early as middle school about whether a student is at-risk of being disengaged with learning and potentially be unable to attend a selective college down the line. Such early indicators may be used to track students' progress, creating the potential for more effective and earlier guidance for students, targeted towards the factors that often prevent students from attending selective colleges despite having excellent qualifications (cf. Hoxby & Avery, 2012).

To the degree that these models can give information not just on whether a student will attend a selective college but also on which factors reduce the probability of that occurring, these models may help both teachers and guidance counselors create more targeted and individual interventions, potentially helping open the doors of selective colleges to a wider diversity of students. Research has indicated that school guidance counselors are receptive and understand the importance of using data analytics (Young & Kaffenberger, 2011). An early warning system for counselors that provides data on learning, emotions and engagement during classroom activities could supplement student information from teachers and parents to aid them in their academic program planning for students. In coordination with teachers, guidance counselors can use this information on middle school learning, academic emotions and engagement to identify students who may be in need of counseling services – for example, persistent negative emotions during online learning may be a symptom of a broader problem. We believe that further research is needed to determine exactly how to best use data from online learning to drive support for learners. As this research goes forward, counseling efforts that consider both cognitive and non-cognitive skills during learning will have the opportunity to aid in providing adequate opportunities in college preparation. Ultimately, our goal as a society should be in preparing every student in their middle school and high school years to take full advantage of the opportunities that our society can afford them; helping students get past challenges of all kinds.

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Table 1

Barron's College Selectivity Rating

Selectivity Rating	Selectivity Description	Required GPA	Required SAT	Example Institution(s)	Number of Students	Number of Institutions in Sample
10	Most Competitive	B or higher	1240 or higher	Columbia, Harvard, Stanford	122	31
9	Highly Competitive+	B or higher	1240 or higher	Cornell University	109	15
8	Highly Competitive	B or higher	1240 or higher	Fordham University	108	23
7	Very Competitive+	B- or higher	1146 to 1238	Yeshiva University	25	11
6	Very Competitive	B- or higher	1146 to 1238	Hunter College	326	29
5	Competitive+	C or higher	1000 or higher	Buffalo State College	30	7
4	Competitive	C or higher	1000 or higher	St. Joseph's College	820	73
3	Less Competitive	C or below C	Below 1000	Berkeley College	72	15
2	Non-Competitive	C or below C	Below 1000	College of Staten Island	1120	66
1	Special			Julliard School	32 (Excluded)	8
	(Unclassified)			Glendale Community College	46 (Excluded)	42

Table 2

Cut-offs for Classes of 'Selective' and 'Not Selective' from Barron's Selectivity Rating

Selectivity Rating	Selectivity Description	Cut-off 1 (I)	Cut-off 2 (II)	Cut-off 3 (III)	Cut-off 4 (IV)
10	Most Competitive	Selective	Selective	Selective	Selective
9	Highly Competitive+	Selective	Selective	Selective	Not Selective
8	Highly Competitive	Selective	Selective	Selective	Not Selective
7	Very Competitive+	Selective	Selective	Not Selective	Not Selective
6	Very Competitive	Selective	Selective	Not Selective	Not Selective
5	Competitive+	Selective	Not Selective	Not Selective	Not Selective
4	Competitive	Selective	Not Selective	Not Selective	Not Selective
3	Less Competitive	Not Selective	Not Selective	Not Selective	Not Selective
2	Non-Competitive	Not Selective	Not Selective	Not Selective	Not Selective

Table 3

Model Performances (AUC ROC) of Urban and Suburban Detectors of Academic Emotions and Behaviors

	Boredom	Confusion	Engaged Concentration	Frustration	Off-Task	Gaming
Urban Detector AUC ROC	0.632	0.736	0.678	0.743	0.819	0.802
Suburban Detector AUC ROC	0.666	0.744	0.631	0.589	0.819	0.802

Table 4
Predictors used in Logistic Regression Model

	Mean	Standard Deviation	Minimum	Maximum
Boredom	0.224	0.071	0.023	0.466
Engaged Concentration	0.642	0.064	0.341	0.937
Confusion	0.082	0.050	0.000	0.371
Frustration	0.144	0.086	0.000	0.514
Off-Task	0.216	0.080	0.065	0.837
Gaming	0.132	0.137	0.004	0.777
Knowledge	0.347	0.213	0.035	0.940
Carelessness	0.206	0.135	0.010	0.799
Correctness	0.459	0.150	0.000	0.946
Number of Actions	722.52	822.38	2	14378

Table 5

Correlations of Independent Variables (*p < 0.05. **p < 0.001)

	Boredom	Engaged Concentration	Confusion	Frustration	Off-task	Gaming	Knowledge	Carelessness	Correctness	Number of Actions
Boredom	1									
Engaged Concentration	-0.347**	1								
Confusion	0.710**	-0.070**	1							
Frustration	0.405**	0.126**	0.317**	1						
Off-task	0.453**	-0.397**	0.170**	-0.049*	1					
Gaming	-0.351**	0.390**	-0.208**	0.173**	-0.503**	1				
Knowledge	-0.390**	0.085**	-0.491**	-0.069**	0.048*	-0.269**	1			
Carelessness	-0.475**	0.145**	-0.500**	-0.003	-0.030	-0.155**		1		
Correctness	-0.134**	-0.055*	-0.348***	-0.230**	0.211**	-0.586**	0.807**	0.673**	1	
Number of Actions	-0.493**	0.477**	-0.332**	0.090**	-0.389**	0.546	0.067	0.178	-0.192	1

Table 6

*Correlations of Going to a Selective College to Independent Variables in Different Cut-offs (*p < 0.05. **p < 0.001)*

	Selective College (I)	Selective College (II)	Selective College (III)	Selective College (IV)
Boredom	-.093**	-.119**	-.057	-.062*
Engaged Concentration	.118**	.159**	.106**	.093**
Confusion	-.239**	-.236**	-.161**	-.108**
Frustration	-.174**	-.176**	-.126**	-.079**
Off-task	.086**	.068**	.073**	.048*
Gaming	-.247**	-.234**	-.197**	-.129**
Knowledge	.408**	.408**	.302**	.204**
Carelessness	.365**	.361**	.263**	.177**
Correctness	.448**	.439**	.331**	.227**
Number of Actions	-.0002	.009	-.026	-.018

Table 7

*Features for Students who Attended Selective College (1) and who did not Attend Selective College (0) (*p < 0.05. **p < 0.001 MS = marginally significant)*

	Selective College		Mean	SD	t-value	Cohen's d		Selective College		Mean	SD	t-value	Cohen's d
Boredom	Cut-Off 1	0	0.237	0.055	9.026**	0.333	**Concentrati**	Cut-Off 1	0	0.640	0.053	-1.906^{MS}	0.071
		1	0.214	0.079					1	0.644	0.072		

	Cut-Off 2	0	0.231	0.064	8.043**	0.406		Cut-Off 2	0	0.640	0.060	-3.204*	0.157
		1	0.203	0.084					1	0.650	0.074		
	Cut-Off 3	0	0.226	0.068	4.238**	0.290		Cut-Off 3	0	0.641	0.062	-1.862 MS	0.125
		1	0.206	0.085					1	0.649	0.075		
	Cut-Off 4	0	0.225	0.070	3.418*	0.379		Cut-Off 4	0	0.641	0.063	-2.596*	0.241
		1	0.198	0.085					1	0.657	0.074		
Confusion	**Selective College**		**Mean**	**SD**	**t-value**	**Cohen's d**	**Frustration**	**Selective College**		**Mean**	**SD**	**t-value**	**Cohen's d**
	Cut-Off 1	0	0.095	0.047	13.254**	0.508		Cut-Off 1	0	0.159	0.074	*8.317**	0.312
		1	0.071	0.050					1	0.132	0.093		
	Cut-Off 2	0	0.088	0.049	12.706**	0.560		Cut-Off 2	0	0.152	0.082	7.912**	0.373
		1	0.061	0.047					1	0.120	0.094		
	Cut-Off 3	0	0.084	0.050	8.241**	0.478		Cut-Off 3	0	0.148	0.085	5.788**	0.358
		1	0.061	0.046					1	0.117	0.092		
	Cut-Off 4	0	0.083	0.050	5.282**	0.489		Cut-Off 4	0	0.145	0.086	4.118**	0.382
		1	0.058	0.046					1	0.0122	0.091		
Off-Task	**Selective College**		**Mean**	**SD**	**t-value**	**Cohen's d**	**Gaming**	**Selective College**		**Mean**	**SD**	**t-value**	**Cohen's d**
	Cut-Off 1	0	0.211	0.084	-2.469*	0.097		Cut-Off 1	0	0.167	0.148	11.647**	0.461
		1	0.219	0.076					1	0.105	0.121		
	Cut-Off 2	0	0.214	0.083	-1.713	0.070		Cut-Off 2	0	0.149	0.144	13.122**	0.488
		1	0.220	0.071					1	0.083	0.101		
	Cut-Off 3	0	0.214	0.081	-2.575*	0.149		Cut-Off 3	0	0.141	0.140	11.781**	0.503
		1	0.226	0.073					1	0.073	0.092		
	Cut-Off 4	0	0.215	0.081	-1.554	0.120		Cut-Off 4	0	0.136	0.138	9.505**	0.527
		1	0.225	0.066					1	0.064	0.078		
Knowledge	**Selective College**		**Mean**	**SD**	**t-value**	**Cohen's d**	**Carelessness**	**Selective College**		**Mean**	**SD**	**t-value**	**Cohen's d**
	Cut-Off 1	0	0.249	0.159	-24.052**	0.893		Cut-Off 1	0	0.151	0.095	-21.137**	0.775
		1	0.423	0.218					1	0.248	0.146		
	Cut-Off 2	0	0.294	0.186	-23.063**	1.082		Cut-Off 2	0	0.176	0.114	-18.634**	0.944
		1	0.503	0.211					1	0.294	0.153		
	Cut-Off 3	0	0.322	0.201	-17.631**	1.024		Cut-Off 3	0	0.191	0.126	-12.932**	0.878
		1	0.528	0.206					1	0.306	0.155		
	Cut-Off 4	0	0.337	0.208	-12.092**	1.121		Cut-Off 4	0	0.200	0.131	-8.763**	0.976
		1	0.569	0.202					1	0.329	0.161		
Correctness	**Selective College**		**Mean**	**SD**	**t-value**	**Cohen's d**	**Number of Actions**	**Selective College**		**Mean**	**SD**	**t-value**	**Cohen's d**
	Cut-Off 1	0	0.385	0.112	-26.424**	0.984		Cut-Off 1	0	698.97	738.47	-1.347	0.051
		1	0.517	0.150					1	740.75	881.66		
	Cut-Off 2	0	0.420	0.128	-25.210**	1.184		Cut-Off 2	0	715.35	806.29	-0.784	0.035

		1	0.577	0.146					1	743.74	868.52		
	Cut-Off 3	0	0.439	0.003	-19.982**	1.160		Cut-Off 3	0	727.42	838.63	0.827	0.048
		1	0.601	0.008					1	687.94	697.04		
	Cut-Off 4	0	0.451	0.144	-14.149**	1.311		Cut-Off 4	0	727.48	834.55	1.459	0.135
		1	0.640	0.152					1	616.39	484.81		

Table 8

Goodness-of-Fit and Performance Values of Selective College Enrollment Model

	R^2 (Cox & Snell)	R^2 (Nagelkerke)	Kappa	AUC ROC
Cut-off 1	0.221	0.296	0.419	0.774
Cut-off 2	0.212	0.313	0.386	0.801
Cut-off 3	0.122	0.230	0.142	0.793
Cut-off 4	0.063	0.204	0.029	0.821

Table 9

Selective College Enrollment Model

	Features	Coefficient	Standard Error	Chi-Square	p-value	Odds Ratio
Cut-off1	Engaged Concentration	.119	.060	3.956	.047	1.127
	Confusion	-.153	.064	5.710	.017	.858
	Frustration	-.206	.053	14.907	<.001	.814
	Gaming	-.186	.077	5.862	.015	.830
	Carelessness	.275	.081	11.628	.001	1.316
	Correctness	.835	.098	72.805	<.001	2.305
	Number of Actions	.200	.064	9.870	.002	1.222
	Constant	.404	.046	76.681	<.001	1.497
Cut-off2	**Features**	**Coefficient**	**Standard Error**	**Chi-Square**	**p-value**	**Odds Ratio**
	Engaged Concentration	.171	.056	9.327	.002	1.186
	Frustration	-.182	.051	12.672	<.001	.834
	Off-task	-.122	.067	3.321	.068	.885
	Gaming	-.230	.104	4.840	.028	.795
	Student Knowledge	.312	.096	10.485	.001	1.366
	Correctness	.831	.123	45.593	<.001	2.296
	Number of Actions	.195	.062	9.841	.002	1.215
	Constant	-.1387	.056	611.729	<.001	.250
Cut-off3	**Features**	**Coefficient**	**Standard Error**	**Chi-Square**	**p-value**	**Odds Ratio**
	Boredom	.267	.102	6.809	.009	1.306
	Engaged Concentration	.160	.066	5.885	.015	1.174
	Frustration	-.277	.091	9.333	.002	.758
	Student Knowledge	.422	.145	8.537	.003	1.526
	Correctness	.728	.136	28.742	<.001	2.071
	Number of Actions	.150	.080	3.497	.061	1.162
	Constant	-2.394	.079	913.297	<.001	.091
Cut-off4	**Features**	**Coefficient**	**Standard Error**	**Chi-Square**	**p-value**	**Odds Ratio**
	Engaged Concentration	.229	.094	5.978	.014	1.257
	Correctness	1.159	.097	144.072	<.001	3.186
	Constant	-3.730	.143	678.318	<.001	.024

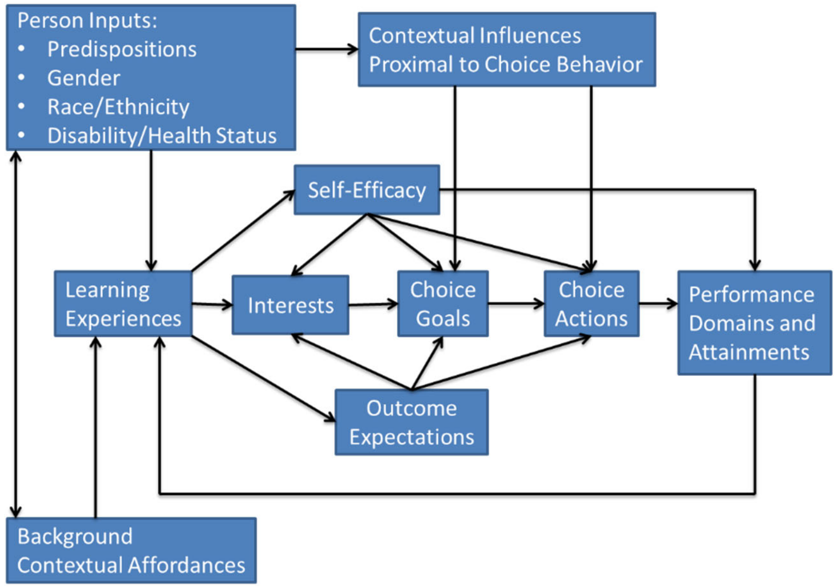

Figure 1. Social Cognitive Career Theory

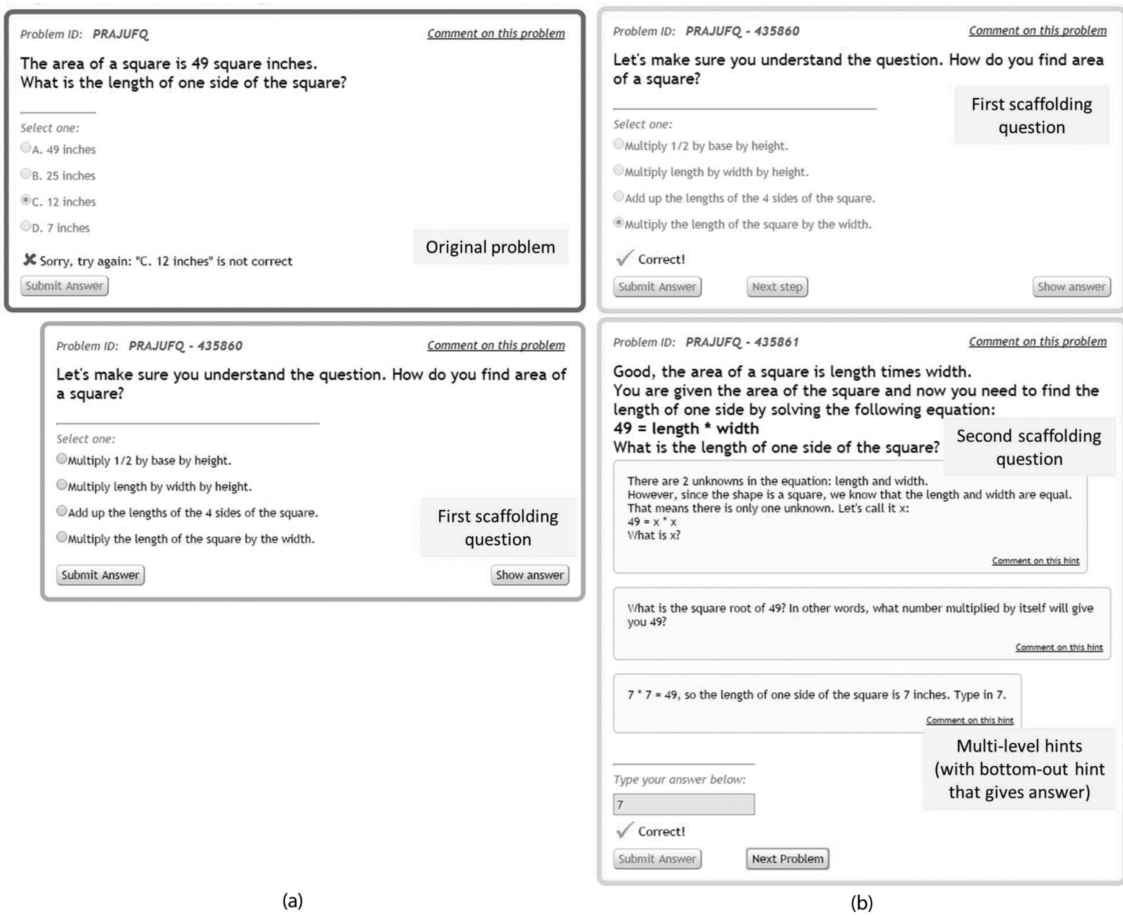

Figure 2. Example of a problem in ASSISTments. a) If a student gets a problem incorrect, hints and scaffolding problems are there to aid the student in eventually getting the correct answer. b) Example of Scaffolding and Hints in ASSISTments.

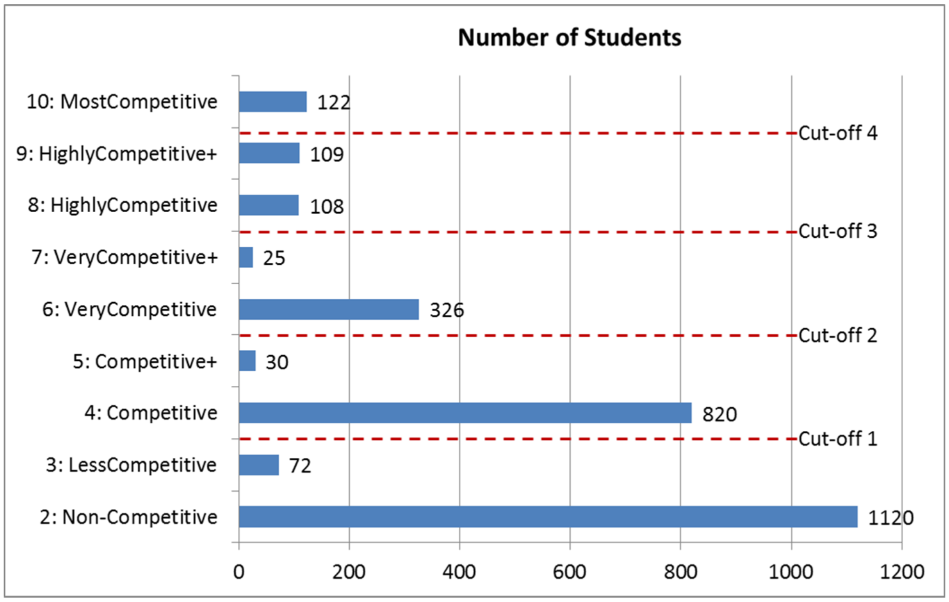

Figure 3. Number of Students in 'Selective' and 'Not Selective' Class for each Cut-Off

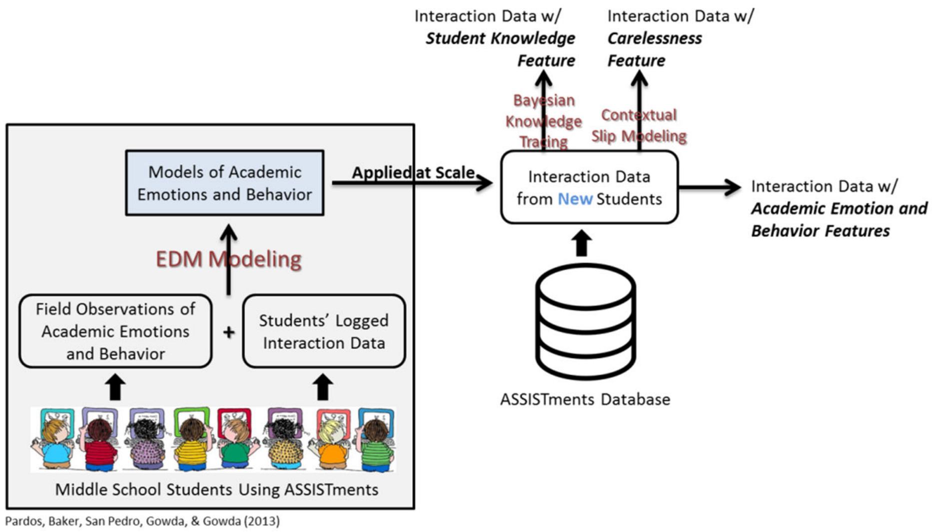

Figure 4. Feature Generation in ASSISTments Interaction Data.

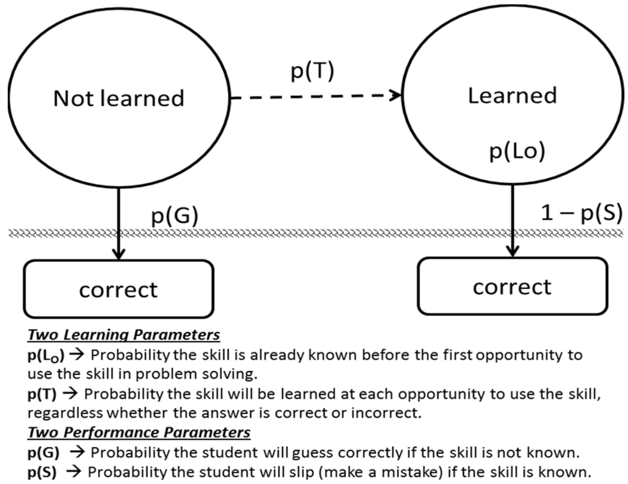

Figure 5. Bayesian Knowledge Tracing.