An Integrated Look at Middle School Engagement and Learning in a Digital Environment as Precursors to College Attendance

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Middle school is an important phase in the academic trajectory, which plays a major role in the path to successful post-secondary outcomes such as going to college. Despite this, research on factors leading to college-going choices do not yet utilize the extensive fine-grained data now becoming available on middle school learning and engagement. This paper uses interaction-based data-mined assessments of student behavior, academic emotions and knowledge from a middle school online learning environment, and evaluates their relationships with different outcomes in high school and college. The data-mined measures of student behavior, emotions, and knowledge are used in three analyses: (1) to develop a prediction model of college attendance; (2) to evaluate their relationships to intermediate outcomes on the path to college attendance such as math and science course-taking during high school; (3) to develop an overall path model between the educational experiences students have during middle school, their high school experiences, and their eventual college attendance. This gives a richer picture of the cognitive and non-cognitive mechanisms that students experience throughout varied phases in their years in school, and how they may be related to one another. Such understanding may provide educators with information about students' trajectories within the college pipeline.

Keywords. Post-Secondary Outcomes, Middle School Learning, Academic Emotion, Engagement, Educational Technology, Educational Data Mining, Learning Analytics

INTRODUCTION

College attendance and completion for many learners often begins with students aspiring to attend or enroll in college. Students go through a longitudinal and complex process of developing these aspirations over the course of elementary, middle and high school (Cabrera & La Nasa, 2000; Hossler, Braxton, & Coopersmith, 1989). Along this pathway to college, students have varied educational experiences that result to either fully realizing their opportunities or falling off this pathway. Many individual characteristics and environmental supports contribute to the differences in college access and attendance among students. Cabrera, La Nasa, and Burkum (2001) showed that the strongest predictors of college access include parental involvement; academic achievement; financial aid; socioeconomic status (SES); participation in college preparatory classes; academic aspirations; and access to guidance counseling. According to Social Cognitive Career Theory (SCCT, Lent, Brown, & Hackett, 1994), 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, and these interests lead to the development of intentions or goals for further exposure and engagement with the activity (Lent, Brown, & Hackett, 1994). In most cases, family background and financial resources have strong, significant impacts on where students find themselves after high school. However, many of these factors are not actionable in terms of being directly changeable by school-based interventions. For this reason, this research attempts to answer Bowers' (2010) call to identify early, less acute signals of disengagement, when student engagement is still amenable to intervention. Specifically, this paper investigates antecedents to college-going that occurs during middle school, using assessments of academic emotions, disengagement, and learning, so that possible paths to re-engagement can be developed before students develop more serious academic problems.

Recent studies have explored assessments of academic emotions, engagement, and learning in fine-grained detail, together with their associations with learning outcomes, within the context of online learning system. Researchers have developed automated models 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. Specifically, these fine-grained assessments of cognitive and non-cognitive factors during middle school have been shown to predict learning gains, performance on standardized exams, and preparation for future learning (Authors, 2010b; Authors, 2013a; Authors, 2013b).

However, there has been limited research on whether these fine-grained measures during middle school are associated to and can predict long-term student outcomes – both in high school and college. Three studies are conducted in this paper to answer the following research questions:

1. Are student behavior, academic emotions and knowledge during middle school computer-based math learning predictive of post-secondary enrollment? (Study 1)
2. Are student behavior, academic emotions and knowledge during middle school computer-based math learning predictive of high school course choices in math and science? (Study 2)
3. What is the role that high school course choices play in the path between middle school indicators and college attendance? (Study 3)

Each study presents an analysis that uses different sets of data from overlapping sets of students collected over the course of several years. More specifically, Study 1 assesses how the postsecondary outcome of college enrollment is associated with malleable factors such as engaged or disengaged behavior, emotions, and knowledge of students within the context of computer-based math learning in middle school. Data on these malleable factors is distilled from students' interaction data from blended learning used in class or as homework during middle school. These measures are then integrated with more recent data on whether the students enrolled in college to create a logistic regression model predicting this postsecondary outcome. Study 2 looks at how the same middle school assessments are associated with high school outcomes gathered from those students – course choice of AP math or AP science. Study 3 then culminates with exploring the path of relationships from these middle school assessments of student behavior, academic emotions and knowledge, to high school course choice of AP math or AP science, to enrollment in college. This analysis leads to the development of an overall path model that combines middle school assessments of student behavior, academic emotions and knowledge from computer-based math learning with the same students' course choices when they were in high school, and with those students' college enrollment.

This paper aims to analyze the relationships of constructs between different educational phases: First, we study the relationship between middle school indicators of learning and engagement, and college attendance; next, we study the relationship between of middle school indicators and high school outcomes; and lastly, we study the role that high school course choice plays in the path between middle school indicators and college attendance. This research leverages data from an online learning environment students used, the ASSISTments system (Razzaq et al., 2005). We assess key aspects of student emotion, engagement, and knowledge by using existing machine-learned models of these constructs previously developed for ASSISTments (Authors, 2013b; Authors, 2014b). Evaluating these factors as early as middle school may provide educators with information about a student's educational progress and facilitate guiding that student towards academic success.

THEORETICAL FRAMEWORK

Social Cognitive Career Theory

The factors that come into play between the students' environment and their learning experiences can be seen within the Social Cognitive Career Theory (SCCT; Lent, Brown, & Hackett, 1994). Based on Bandura's (1986) general social cognitive theory, the SCCT model asserts that academic and career choices are shaped throughout middle school and high school by environmental supports and barriers, as well as the students' self-efficacy, outcome expectations, goals, and interests (see Figure 1). SCCT posits that higher levels of interest emerge in contexts where the individual has higher expectations of self-efficacy and outcome expectations, with these interests leading to the development of intentions or goals for further exposure and engagement with the activity (Lent, Brown, & Hackett, 1994). This means that activities that contribute to positive experiences and higher self-efficacy in students help form their interests and engagement in those activities. Conversely, students avoid and become less interested in activities that lead to negative outcomes and a decrease in self-efficacy.

Hence, it can be posited from the SCCT model that interest mediates between self-efficacy and student choices, with self-efficacy in turn mediating between student performance (part of the learning experiences) and the formation of interests – suggesting that positive and meaningful learning experiences can increase self-efficacy, inform interests, and influence a student's choice actions (actual activities a person engages in to execute a choice; Lent, Brown, & Hackett, 1994) (Lent, Brown, & Hackett, 2000). It is thus important to identify factors that govern students' learning experiences prior to making choices related to college outcomes, and evaluate how these experiences contribute to their self-efficacy, interest and student choices.

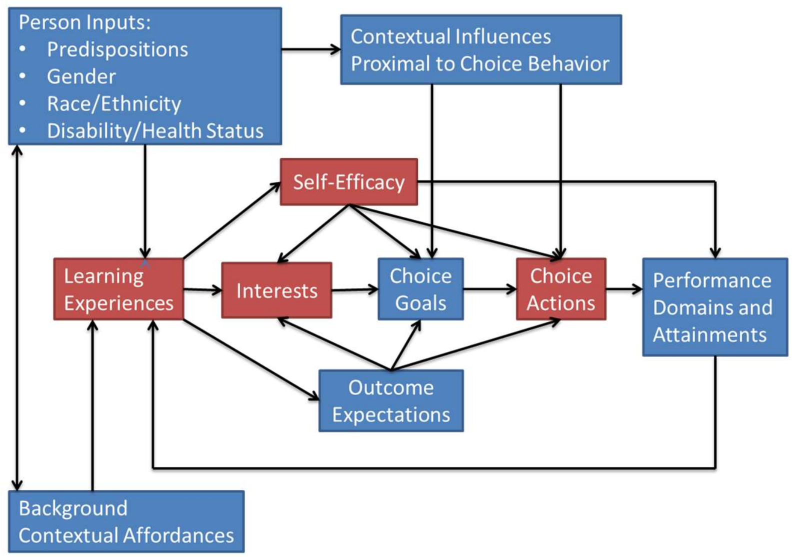

Figure 1. Social Cognitive Career Theory (SCCT).

SCCT research has mainly focused on high school or college students, despite studies that show students starting to develop their abilities and interest in pursuing their postsecondary studies and advanced careers during middle school (Cabrera, La Nasa, & Burkum, 2001; Camblin, 2003). Students who start thinking about college as early as middle school tend to become interested in achieving a good academic record. As early as middle school, students may plan to take appropriate courses or extracurricular activities once they are in high school that will contribute to their college applications (Roderick, Coca, & Nagaoka, 2011). According to Conley (2007), reaching college readiness, the level of preparation a student needs to succeed at the postsecondary level without remediation, is based on building key cognitive skills (e.g. problem solving, reasoning, analysis, interpretation, intellectual openness) and content knowledge in subject areas such as English, Math, Science and Social Sciences (Conley, 2007). Both academic and nonacademic factors are relevant. Thus, it is important to align expectations for high school graduation with college and career requirements, and important that students develop core cognitive skills to be college-ready (Conley, 2008; Conley, Lombardi, Seburn, & McGaughy, 2009).

Equally important in preparing for college is considering what Farrington and colleagues (2012) identified as non-cognitive factors that are influential to students' long-term success: academic behaviors, academic perseverance, academic mindsets, learning strategies, and social skills. They argued that such factors are malleable and receptive to contextual influences. Hence, understanding students' post-secondary outcomes necessitates considering non-cognitive factors in their learning experiences such as academic emotions and engagement. These factors are as-yet under-considered in career development models like SCCT.

Thus, it can be argued that factors such as knowing a skill, academic emotions and student engagement during middle school may play an influential role in the processes involved in SCCT, and therefore may contribute to the eventual decision to attend college. In SCCT, students' vocational choices are influenced by their interests that are developed from their self-efficacy, attitudes, and goals for career development (i.e., college enrollment). Students' self-efficacy, attitudes, goals and choices can be seen as themselves influenced by students' engagement when they encounter increasingly sophisticated domain content (see examples in Authors, 2008b; McQuiggan, Mott, & Lester, 2008).

Learning Analytics and Educational Data Mining in Education

The growth of new technologies used in the educational context (e.g. online learning, educational games, learning management systems) has led to the increasing quantity of data captured that can be used for research in exploring patterns of different educational phenomena. Researchers in educational data mining (EDM) or learning analytics (LA) extract useful and actionable information from such large databases or datasets by adopting methodologies from data mining, machine learning, data visualization, psychometrics and other areas of statistics (Authors, 2014a).

In the educational setting, approaches in learning analytics are often used to make operational decisions to improve educational outcomes (e.g. academic performance, attendance, graduation rates, retention rates, etc.) – for example, identifying students who are at risk for failure or dropout, predicting student performance, predicting whether a student will graduate on-time, examining indicators of readiness for college and career, or personalizing instruction in classrooms. These types of analyses and predictions have become particularly common in higher education systems that make use of virtual learning environments (VLEs) or learning management systems (LMSs). For example, Purdue University's Course Signals is a student success system that aims to help students understand their progress early enough to be able to seek help or take a different approach in their learning (Arnold & Pistilli, 2012). The system uses data from its student information system (SIS), the points earned so far by the student in learning activities, student effort from student interactions with an LMS, prior academic history, and standardized test scores, to output an appropriate traffic 'signal' – red indicates a high likelihood of failure, yellow shows potential problems, green indicates a high likelihood of success. Another analytics platform from CIVITAS Learning is used in higher education and provides a variety of student support such as degree planning, identifying at-risk students, as well as providing administrative analytics such as predictions of retention across whole student populations, using multiple sources of data (academic records, SIS, communications from campus faculty) to develop a comprehensive view of the student (Milliron, Malcolm, & Kil, 2014). In another effort, a charter school in New York City adopted a learning analytics reporting intervention tool, called the Bridge Report, for academic intervention by educators and to communicate with students' families (Hawn, 2015). The Bridge Report integrates in one report several important indicators such as quarterly GPA, absences, tardiness, discipline incidents, test scores, reading assessment scores, and Grade Level Equivalents in reading and math. The Bridge Report presents scores using the same color-coded indicators as Course Signals, with thresholds for intervention defined by the school.

EDM methods have been used to develop fine-grained models of student individual differences in areas such as knowledge (Corbett & Anderson, 1995; Khajah, Lindsey, & Mozer, 2016), engagement (Authors, 2008b; Authors, 2013b; D'Mello et al., 2008; Sabourin et al., 2011), and meta-cognition (Aleven et al., 2006; Vaessen, Prins, & Jeuring, 2014), that have been traditionally investigated at a coarse-grained level, through measures like questionnaires given out of context or end-of-year tests. Educational technologies that offer large-scale, fine-grained interaction data have enabled researchers in recent years to apply EDM methods in developing fine-grained models of these constructs. (Details of how these constructs can be modeled will be demonstrated in the succeeding sections for a specific online learning system.) Through these systems, such as ASSISTments (Razzaq et al., 2005), ALEKS (Canfield, 2001) and the Cognitive Tutor (Koedinger & Corbett, 2006), students produce a series of actions as they complete learning activities, yielding a rich source of data that can support researchers in investigating whether students' strategic choices and behaviors translate into learning, providing the potential for rich, multi-faceted, and fine-grained models of these constructs (Clarke-Midura & Dede, 2010). These fine-grained models are often developed to enable systems to respond to individual differences for these constructs and improve student learning, and/or to examine how these constructs correlate to learning and achievement both within educational software (e.g. within-system learning) and beyond the context of the educational software (e.g. performance on state exams) (Feng, Heffernan, & Koedinger, 2009).

Fine-grained types of models have been developed for a range of constructs – such as learning (i.e. student knowledge), academic emotions, and student behavior. **Student knowledge** is estimated as how well a student knows a specific skill (or a knowledge component) at a specific time based on their previous experience with that skill (Corbett & Anderson, 1995). **Academic emotions**, the emotions experienced during learning and classroom instruction (Pekrun & Linnenbrink-Garcia, 2012), also referred to as affect or affective states, can also play an important role in learning outcomes. Examples include *boredom*, which is prominent in many middle school classrooms (Authors, 2013b; Pekrun et al., 2010; Rowe et al., 2009). A second affective state, *engaged concentration*, related to Csikszentmihalyi's flow state (1990), describes the state when a student has intense concentration, focused attention, and complete involvement in the task at hand (Authors, 2010b). Another is *confusion*, where a student encounters a mismatch in their understanding between their prior knowledge and incoming information, creating a cognitive disequilibrium in students (D'Mello et al., 2014; Rozin & Cohen, 2003). Students can also experience *frustration* (Kort, Reilly, & Picard, 2001) which, like confusion, promotes cognitive disequilibrium in students, where they have feelings of distress when tasks 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 disengaged behaviors in classrooms. *Gaming the system* is a behavior when a student exploits the properties of a learning activity (e.g. systematic guessing or hint abuse to get the answers within an educational software) to obtain the solution (Authors, 2006). Another disengaged behavior is *off-task behavior*, where students engage in extraneous activities and completely disengage from their learning task (Authors, 2004; Karweit & Slavin, 1982). Students have also been found to exhibit *careless behavior* when they make errors on questions despite knowing how to successfully answer them (Authors, 2011; Clements, 1982). These academic emotions and disengaged behaviors, have been found to be associated with learning, achievement and motivational outcomes both within and outside educational software (Authors, 2010b; Authors, 2013b; Craig et al., 2004; Pekrun et al., 2010; Fredericks, Blumenfeld, & Paris, 2004).

Assessments developed using EDM have been shown to predict educational outcomes such as learning gains (Authors, 2004; Authors, 2009; Sabourin, Mott, & Lester, 2011) and standardized exams (Authors, 2013b; Fancsali, 2014). However, their associations with long-term student outcomes have only been studied in a small number of studies. Fine-grained measures of constructs in the students' learning experiences may also be able to predict eventual long-term outcomes, such as the transition from middle school to high school to college. Even grades alone can predict outcomes across this period (e.g. Bowers, 2010), much less the richer models made possible by educational data mining on interaction logs. In this paper, we attempt to model a college outcome (i.e. enrollment) using fine-grained measures of academic emotions, student behaviors and learning derived from a student's learning experiences with a math educational software back when they were in middle school. The data used in these measures was obtained years before the measures were developed, a powerful advantage of applying educational data mining methods to retrospective log files. Such methods make longitudinal analysis easier, as not all measures need to be known and derived in advance of data collection.

Hence, factors in a student's learning experiences have the potential to play an important role in the development of academic and career self-efficacy, interests, and choice actions (Lent, Brown, & Hackett, 1994). We hypothesize in this paper that particular aspects of student behaviors, academic emotions and knowledge in middle school that define students' *learning experiences* contribute to *self-efficacy*, *interests*, and their *choice actions* (Lent, Brown, & Hackett, 1994) (course taking in high school and college enrollment in this study) from the SCCT model, and can serve as additional information and predictors in current models for college and career pathways (Figure 2).

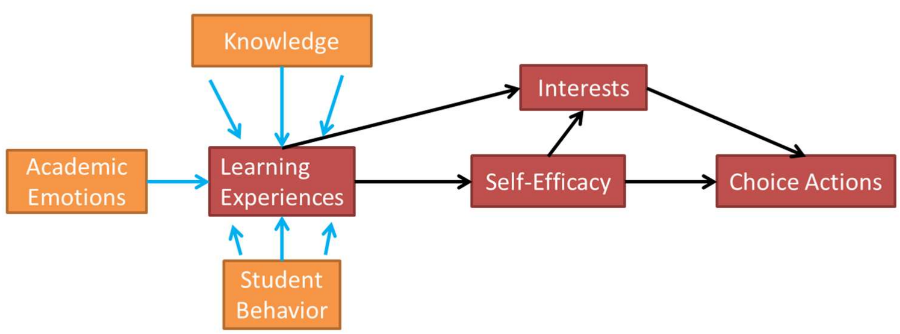

Figure 2. Hypothesized potential roles played by academic emotions, knowledge, and student behavior in SCCT.

THE ASSISTMENTS SYSTEM

The ASSISTments system (Figure 3) (Razzaq et al., 2005) is a tutoring system for middle school mathematics developed at Worcester Polytechnic Institute (WPI). This free web-based educational system aims at *assessing* knowledge and proficiency of its student users while *assisting* them in their problem solving and learning. The 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 (Razzaq et al., 2005). Within the system, each mathematics problem maps to one or more knowledge components or mathematical skills that cover a range of areas in mathematics, including algebra, probability, number sense with fractions and decimals, geometry, and graph interpretation to name a few. 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 last step of scaffolding returns the student to the original question (as in Figure 4). Once the correct answer to the original question is provided, the student is prompted to go to the next question.

ASSIStments provides teachers with detailed reports and summaries on mathematical skills each student learns for assessment and diagnostic purposes. Students are guided and instructed by teachers trained in formative assessment, assisted by ASSISTments team members who visit classrooms on a weekly basis and assist in implementing the software in classrooms. These teachers use ASSISTments in their math curricula for review of concepts and test preparation.

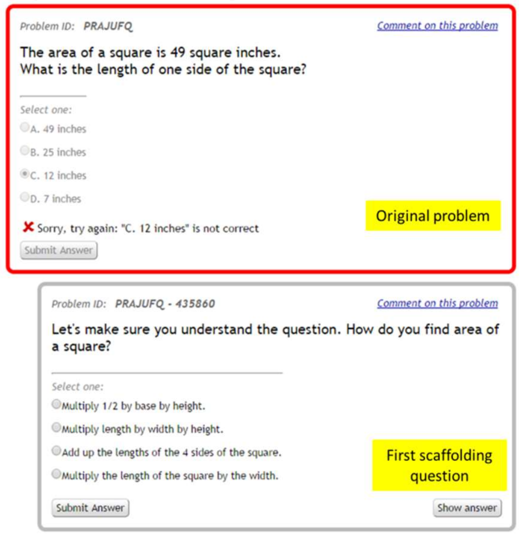

Figure 3. Example of an ASSISTments problem.

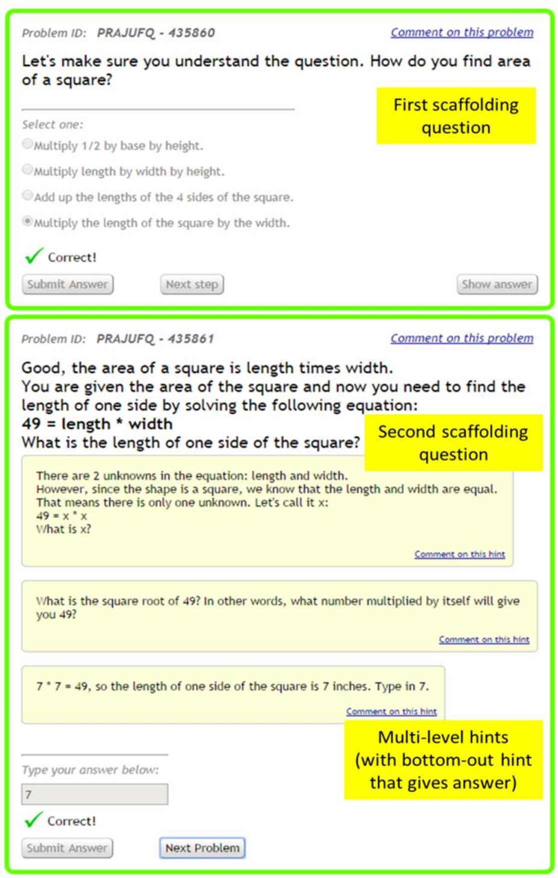

Figure 4. Example of scaffolding and hints in an ASSISTments problem.

MIDDLE SCHOOL, HIGH SCHOOL AND COLLEGE DATA

A range of constructs were assessed from the interaction data of ASSISTments including student knowledge, academic emotions, disengaged behaviors, and other information on student usage, to form the variables used in predicting student high school course-taking and post-secondary enrollment.

Student Sample

A full student sample of 7,636 students who used ASSISTments when they were in middle school from school years 2004-2005 to 2008-2009 was used for this research (Table 1). They were in four school districts in the Northeastern United States that used the ASSISTments system throughout a single school year (two to three school years for a number of students). Two districts were urban with large proportions of students requiring free/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 teacher-led classes held in their school's computer lab. In one suburban district, 8th graders used the system 40 mins each day in an extra class, rather than in their regular class. As mentioned, ASSISTments was used for review of math concepts and test preparation. Overall, these students made over 6 million actions within the software (where an action consisted of making an answer or requesting help), within an estimated total of over 2 million mathematics problems (counting both original and scaffolding problems), working on an average of over 250 problems per student.

Table 1

Breakdown of Student Sample (n = 7636 students)

	Urban School District 1 (n = 5675)	Urban School District 2 (n = 308)	Suburban School District 1 (n = 1259)	Suburban School District 2 (n = 394)
Caucasian	34%	35%	64%	88%
African-American	15%	5.4%	1.9%	3.4%
Hispanic	40%	47%	6.3%	5.3%
Asian	7.5%	5.7%	24%	2.1%
Free or reduced price lunch	High	High	Low	Low
State exam performance	Low	Low	High	High
English as second language	High	High	Low	Low
College readiness	Below Average	Below Average	Above Average	Below Average
Math proficiency	Below Average	Below Average	Above Average	Average

As will be explained in the subsequent sections, the models created for Study 1, Study 2 and Study 3 each derived its modeling sample from this full student sample of 7,636 students, differing in the outcome variables used for each model (different number of high school and college variable were available for the different student subsets).

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

The ASSISTments system was the primary source of middle school data. The middle school variables were derived from the interaction or log data of the full student sample who used the ASSISTments system (7,636 students).

The academic emotions consisted of four variables: boredom, engaged concentration, confusion, and frustration. The student behaviors consisted of three variables: off-task behavior, gaming the system, and carelessness. Except for correctness and number of actions, each of these variables were inferred using previously-developed interaction-based models for ASSISTments first reported in (Authors, 2013b; Authors, 2014b). 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. All of the middle school variables were then aggregated (i.e. averaged) into a set of single overall assessments for each student.

Figure 5 shows how models of our middle school variables were developed for ASSISTments and subsequently computed from the ASSISTments interaction data. The models of academic emotions and behavior are identical to the models developed for ASSISTments first reported in (Authors, 2013b; Authors, 2014b).

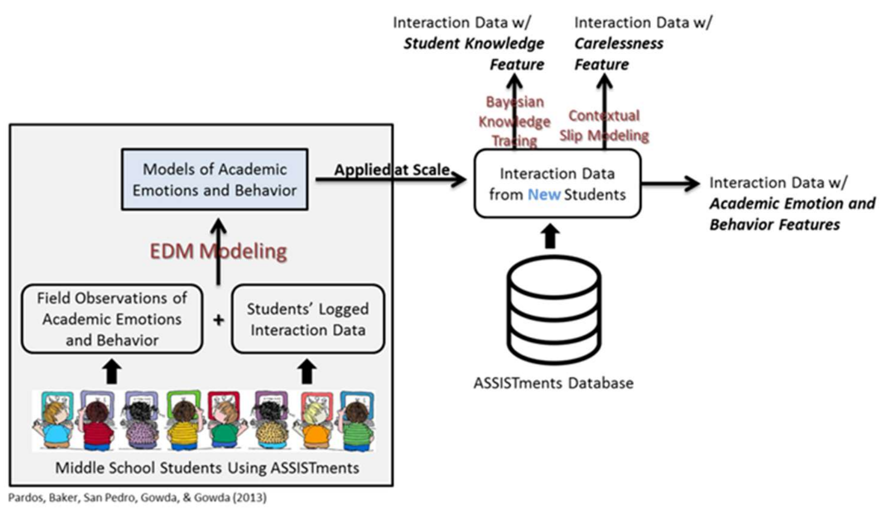

Figure 5. Feature generation in ASSISTments interaction data.

Modeling Student Knowledge.

Student knowledge was derived from tutor usage in ASSISTments by applying Corbett and Anderson's (1995) Bayesian Knowledge Tracing (BKT) model (Figure 6) to the data using brute-force grid search for model fitting (see

Authors, 2010a). BKT infers students' latent knowledge from their performance on problems. 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, 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.

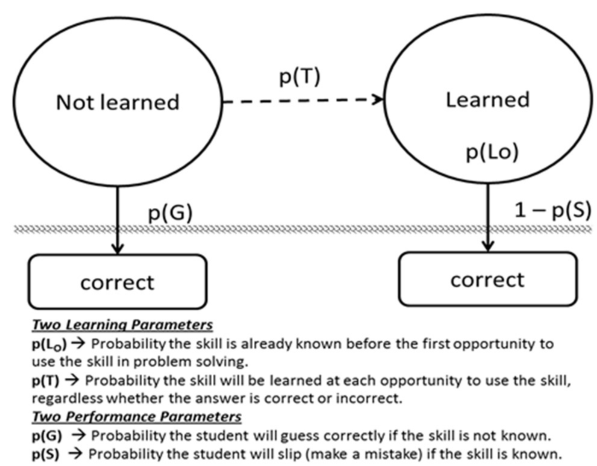

Figure 6. Bayesian Knowledge Tracing.

Modeling Academic Emotions and Disengaged Behavior.

The academic emotions modeled within ASSISTments consist of *boredom*, *confusion*, and *engaged concentration*. The disengaged behaviors modeled consist of *gaming the system*, *off-task behavior*, and *carelessness*.

For the ASSISTment system, separate models were developed for each academic emotion based on the students' location – one model per emotion for students in urban schools, one model per emotion for students in suburban schools, and one model per emotion for students in rural schools (only the urban and suburban models were used in this study). This is based on evidence that urban, suburban, and rural students manifest their emotions differently in online learning (Authors, 2014b). Models derived on urban students (Authors, 2013b) were used to measure academic emotions within students in this study who attended urban schools; models derived on suburban students (Authors, 2014b) were applied to data from students in this study who attended suburban schools. For gaming the system and for off-task behavior, these behaviors were assessed using models generated on urban students alone (the original models), based on evidence of validity for both populations (Authors, 2014b).

These models or detectors were initially developed using a three-stage process: first, field observers noted down student engagement and academic emotions while students used ASSISTments. These observations were collected using the BROMP protocol for quantitative field observation of emotion and engagement and the HART field observation app for Android (Authors, 2015b); 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 techniques were used to create models that could predict the field observations (i.e. academic emotions and engagement) from the log files.

An inter-rater reliability session was conducted at the beginning of data collection, where the two coders coded the same student at the same time, 51 times. The resulting inter-reliability from this session was acceptably high, with Cohen's Kappa of 0.72 for categories of academic emotions (agreement 72% better than chance), and a Cohen's Kappa of 0.86 for categories of student behavior (agreement 86% better than chance). For the urban set of models, field observations of academic emotions and behavior were conducted in an urban middle school in New England, sampled from a diverse population of 229 students. These observations were used to develop and validate models of boredom, engaged concentration, confusion, frustration, off-task behavior, and gaming the system. For the suburban set of models, field observations of academic emotions and behavior were conducted in three suburban schools in New England, sampled from a total of 243 students.

Next, both the handhelds and the educational software logging server were synchronized to the same internet time server during observations, allowing logged student actions to be precisely correlated to the observations. The original log files consisted of data on every student attempt to respond (and whether it was correct), and requests for hint and scaffolding, as well as the context and time taken for each of these actions.

Finally, educational data mining methods (see more details in Authors, 2013b; Authors, 2014b) were used to develop automated detectors (models) of academic emotions and disengaged behaviors 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 research.

Each of the models of academic emotions and behaviors used combinations of features engineered from raw information (e.g. action is a hint, first attempt at a problem is a help request, etc.) to make predictions of that emotion or behavior. Common classification algorithms in educational data mining employed with feature selection were used, choosing the model with the best performance (AUC ROC metric computed using the A' method– Hanley & McNeil, 1982). Each of these models were cross-validated by repeatedly building them on training data composed of a subset of the available data (4/5 of the 229 urban students; 4/5 of 243 suburban students), and applying them on the test data – the other 1/5 of the students – using the goodness metric AUC ROC to select the best model for each construct (shown in Table 2). The algorithms chosen between for each construct included J48 decision trees, logistic regression, JRip, Naïve Bayes, REP-Trees, and K-Star (Witten & Frank, 2005). For example, the gaming model, built using the K-Star algorithm, had a cross-validated AUC ROC of 0.802; as such, it could distinguish a gaming student from a non-gaming student 80.2% of the time.

Table 2

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

	Boredom	*Engaged Concentration*	*Confusion*	*Frustration*	*Off-Task*	*Gaming*
Urban Model AUC ROC	0.632	0.678	0.736	0.743	0.819	0.802
Suburban Model AUC ROC	0.666	0.631	0.744	0.589	N/A	N/A

Assessment of carelessness was created differently than the other models. 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, by estimating the probability that a student answered incorrectly despite actually knowing how to answer correctly (Authors, 2008a; Authors, 2011), using a combination of the probability of student knowledge (from BKT described above) and the pattern of correct and incorrect responses.

High School Variables: AP Math and AP Science Course Choices

Students who used ASSISTments during their middle school years and who were in high school at the time of data collection were administered a short questionnaire that asked the highest level of math and science courses that the student completed in high school. Students who used ASSISTments when they were in middle school during school years 2007-2008 and 2008-2009 completed the questionnaire between the fall of 2012 and the spring of 2013. Surveys were only given to the high schools with the largest proportion of these students, and data was lost by one school district after the administration of the surveys. 282 students attending high schools in the same urban or suburban districts in Northeastern US completed the questionnaires.

Two high school variables from the high school survey were used for this research study – AP Math and AP Science, coded in binary format. AP Math values were based on the question, "What mathematics course are you taking right now? If you are not taking a mathematics course now, what is the last (most recent) mathematics course you took?" The answers to this survey question varied from regular math courses (value = 0, ex. Discrete Math, Math 4) to AP or Honors math courses (value = 1, ex. AP Statistics, Honors Calculus). AP Science values were based on a similar question asking about their high school science course choice. The answers to this survey question also varied from regular science courses (value = 0, ex. Environmental Science, Physics) to AP or Honors science courses (value = 1, ex. AP Biology, AP Chemistry). This measure did not take into account that a student may have taken AP courses before the current class, i.e. taking AP Physics as a junior, and taking Regular Biology as a senior.

College Enrollment

College enrollment records for 2014 for the entire student sample (7,636 students) were obtained from the National Student Clearinghouse. This data included whether a student was enrolled in a college or not, the name of the university, date of enrollment, and college major enrolled in if available (however, this information was seldom available). A subset of the student sample was used in a preliminary study to predict college enrollment from interaction with ASSISTments (Authors, 2013c). Compared to that previous study, this research now included students who used ASSISTments in subsequent years (2007-2008 to 2008-2009). Only the most recent post-secondary institution the student enrolled in was used for this.

The measures obtained for students during middle school, high school and college were combined into a single integrated data set for the 7,636 student sample. Each of the 7,636 students had data for both middle school and college. However, out of the 7,636 students, only 282 students had data for all the phases – values for all middle school variables, all high school variables, and college enrollment. With the large amount of missing data for the high school variables (95% or more of the entire student sample), it was unclear that data imputation would be reliable for this set of variables. Hence, different student datasets formed the basis of the analyses and modeling conducted in Studies 1 to 3 – creating data sets with varying sample sizes. Study 1 created a logistic regression model that predicted college enrollment using data for all students where both the middle school and college data was available (n = 7636 students). Study 2 created two logistic regression models that predicted two high school course choice (AP Math and AP Science) using middle school information (n = 282 students). Finally, Study 3 created two path models that showed the path from middle school variables to college enrollment, one via high school AP Math course choice, and the other via AP Science course choice (n = 282 students). In addition, it is important to note that each model in this study used all urban and suburban students who had the relevant data, rather than creating separate models for each study for each category of school or for each of the four districts (two urban school districts, two suburban districts) in each data set. Splitting the sample into four groups for each study would result in low statistical power for each study, especially for studies 2 and 3 that have an overall sample of only 282 students.

STUDY 1: MODELING COLLEGE ATTENDANCE

The research question for study 1 – *Are student behavior, academic emotions and knowledge during middle school computer-based math learning predictive of post-secondary enrollment?* – was answered by modeling whether a student enrolled in college or not. These outcomes were modeled using the student's interaction-based measures of knowledge, academic emotions and behavior when the student was in middle school and used the ASSISTments system. A logistic regression model was tested and evaluated using the middle school variables as the independent variables and college enrollment as the dependent variable for 7,636 students. In this sample, 54.1% of students were enrolled.

Methods

Measures of middle school student knowledge, academic emotions (boredom, confusion, engaged concentration, frustration), behavior (off-task behavior, gaming the system, carelessness), as well as overall student correctness (a proxy for short-term academic success), and the number of actions made by the student, a proxy for overall usage were used as features within multiple-predictor logistic regression model. Specifically, this larger-scale model was fitted to predict college enrollment using the average of the student's value for each of the predictors across the year (in other words, taking the average boredom per student, average confusion per student, etc.), see Figure 7.

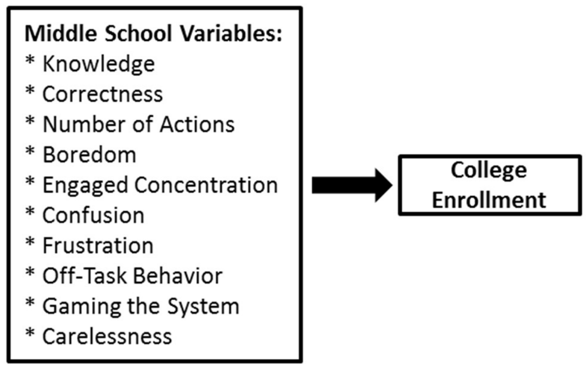

Figure 7. Model design for Study 1 using middle school variables.

We used logistic regression analysis since we have a dichotomous college outcome variable. Choosing logistic regression allows for relatively good interpretability of the resultant models, while matching the statistical approach used in much of the other work that has made predictions of enrollment and success in higher education and analyzed educational pathways (Authors, 2013c; Cabrera, 1994; Nunez & Bowers, 2011;).

The final models created for Study 1 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 cross-validation of models at the student level was conducted to estimate how well the models can be expected to perform when applied to new students not used to build them. Each model's quality was assessed using two metrics, AUC ROC (see above) and Cohen's Kappa. 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; unlike AUC ROC, Cohen's Kappa does not take model confidence into account.

Each cross-validated model was also a result of refining the full set of features into a more parsimonious model. We selected which variables to include in our prediction models using a variable selection approach for logistic regression that chose the model with the largest number of variables where all its variables are statistically significant. Specifically, we used forward stepwise selection for logistic regression (Hosmer & Lemeshow, 2013), starting with a model with a single variable, and progressively adding variables in the model based on the probability of the likelihood-ratio statistic based on the maximum partial likelihood estimates. Forward selection produces good models while searching a relatively limited subset of the space, avoiding the time cost and risk of over-fitting inherent in searching the entire space.

Since maximum likelihood estimates are computed when creating a logistic regression model, pseudo-R^2 statistics which are based on likelihood are also used to evaluate the goodness of fit of each of these logistic regression models, instead of the R^2 used in linear regression which uses the least-squares approach to minimize error. Specifically, we use the Cox & Snell and the Nagelkerke's pseudo-R^2, which indicate how useful the explanatory variables are in predicting the response, quantifying the amount of variance explained by the logistic regression model. These statistics are provided, together with cross-validated AUC ROC and cross-validated Kappa.

All predictor variables were standardized (using z-scores), in order to increase interpretability of the resulting odds ratios (note that this does not impact model goodness or predictive power in any fashion). Standardizing the predictors enables us to show a clear indication of each predictor's contribution to the class variable (college enrollment).

Results

Our final college enrollment model achieved a cross-validated AUC ROC of 0.687 and cross-validated Kappa value of 0.266. This was statistically significantly better than a null model (intercept-only model), and achieved a fit of R^2 (Cox & Snell) of 0.106 and R^2 (Nagelkerke) of 0.141. These values indicate that the final model's predictors explain 10.6% to 14.1% of the variance in whether a student attended college. Note that for our models, our R^2 values serve as measures of effect sizes.

Table 3

College Enrollment Model

Features	***Coefficient***	***Standard Error***	***Chi-Square***	***p-value***	Odds Ratio
Carelessness	-.742	.113	42.846	<.001	.476
Gaming the System	-.431	.041	108.187	<.001	.650
Frustration	-.167	.033	25.282	<.001	.846
Off-task	-.139	.032	18.675	<.001	.870
Boredom	.111	.043	6.717	.010	1.118
Correctness	.377	.058	41.733	<.001	1.458
Knowledge	.581	.126	21.336	<.001	1.787
Number of Actions	.591	.039	230.411	<.001	1.806
Constant	.186	.024	58.384	<.001	1.205

As seen in Table 3, students who had higher knowledge, correctness, number of actions, and boredom when they used ASSISTments in middle school were more likely to attend college, while students who were higher in carelessness, gaming the system, frustration or off-task behavior were less likely to attend college.

In terms of student performance and learning, the model results for student knowledge and correctness to college attendance show that successful demonstration of knowledge within ASSISTments during middle school is more common in students who attended college. The likelihood of college enrollment increasing with boredom once the other variables are taken into account may seem counter-intuitive, but this may be because once we remove unsuccessful bored students, all that may remain are students who become bored because the material is too easy (Authors, 2013b). The model results for variables carelessness, gaming the system, frustration, and off-task behavior show that when they are not addressed properly, they may have negative influences on student learning. Students who experience frustration and remain frustrated are less likely to learn (D'Mello et al., 2008). It is also not surprising that gaming the system was more frequent among students who did not attended college, since gaming the system is known to be associated with poorer learning (Authors, 2009), and poorer performance on standardized state exams (Authors, 2013b).

Discussion

For Study 1, the positive relationships found between middle school knowledge and performance and college enrollment accord with past research studies that used other indicators of academic performance (cf. Carnevale & Rose, 2003; Griffith & Rothstein, 2009) – studies that identify college readiness as being linked to high performance during schooling (Roderick, Nagaoka, & Coca, 2009), and studies that predict that college enrollment is correlated with indicators of aptitude (Eccles, Vida, & Barber, 2004). In addition, the positive relationship between middle school engaged concentration and college enrollment aligns with previous work that finds that students who are more engaged in school tend to have higher academic motivation and achievement (Authors, 2013b; Fredericks, Blumenfeld, & Paris, 2004) that can lead to better preparation for college readiness (Balfanz, 2009; Conley, 2007).

Study 1's findings also provide insights on how interventions can be designed for the middle school factors associated with college enrollment. While researchers have studied disengaged behavior that leads to disciplinary referrals (Kellam et al., 1998; Reinke & Herman, 2002), the cognitive and non-cognitive factors studied in Study 1 may be more frequent, relatively more mild in nature, and are likely more actionable as well. This suggests that in-the-moment interventions provided by software (or suggested by software to teachers) may have unexpectedly large effects, if they address negative affect and disengagement (cf. Authors, 2015a; Arroyo et al., 2007; Lehman, D'Mello, & Graesser, 2012). Students who experience negative emotions can be supported in developing emotional self-regulation skill or can be supported by using alternative instructional strategies or curriculum methods that address confusion and frustration. Students who are bored can be given content with greater novelty or challenge to increase their level of engagement and interest with the learning activities.

STUDY 2: MIDDLE SCHOOL KNOWLEDGE, ACADEMIC EMOTIONS, BEHAVIOR VS. HIGH SCHOOL COURSE CHOICE

The research question for Study 2 – *Are student behavior, academic emotions and knowledge during middle school computer-based math learning predictive of high school course choices in math and science?* – was answered by using interaction-based measures of knowledge, academic emotions, behavior, correctness and usage from 282 students who used the ASSISTments system when they were in middle school, and who also had high school data of their high school course choice in AP Math and AP Science. The ten middle school variables of the 282 students showed similar characteristics as in Study 1.

Around half of the student sample took regular math (n = 141) and science (n = 152) courses when they were in high school, and the other half took AP/Honors math (n = 141) and science (n = 130) courses.

Methods

Like in Study 1, logistic regression analysis was used to create two prediction models for the high school outcomes of AP Math and AP Science course choice, using middle school indicators of performance and engagement (Figure 8). The same cross-validation, feature selection and performance metrics were used for the measures from the 282 students in Study 2.

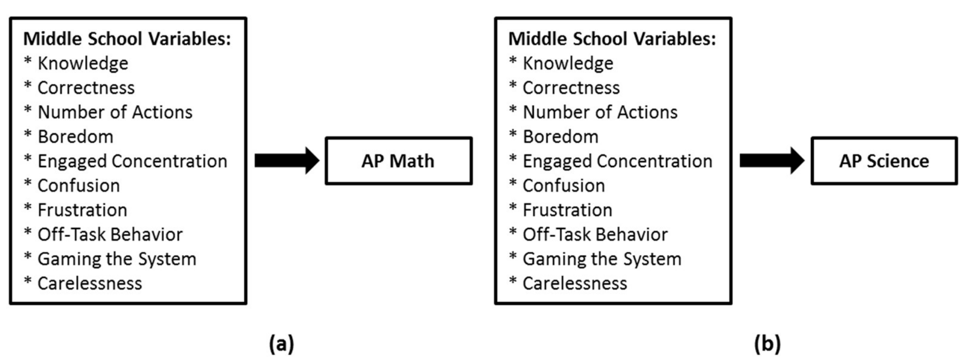

Figure 8. Model designs for Study 2 using middle school variables: (a) Predicting high school course choice of AP Math, (b) Predicting high school course choice of AP Science.

Results

Study 2 looked at high school survey variables AP Math and AP Science and their relationships with middle school measures of knowledge, academic emotions, behavior, correctness and usage. In particular, two models predicting enrollment in an AP Math course and enrollment in an AP Science course during high school were created for 282 students.

AP Math and AP Science Models

The final model for AP Math course choice in high school (Table 4) achieved a cross-validated A' of 0.842 and a cross-validated Kappa of 0.546. This model is statistically significantly better than the null model (χ^2(df = 3, N = 282) = 119.273, $p < 0.001$) and achieved a fit of R^2 (Cox and Snell) = 0.304, R^2 (Nagelkerke) = 0.405, indicating that its predictors explain 30.4-40.5% of the variance of those took AP Math in high school. The combination of middle school variables that best predicts AP Math course choice in high school consisted of knowledge, correctness and off-task, where students who exhibited more knowledge and correctness were more likely to take an AP Math course in high school, while students who were more off-task were more likely to take a regular Math course in high school.

Table 4
Model Results Predicting AP Math Course Choice in High School (n = 282 students)

Features	***Coefficient***	***Standard Error***	***Chi-Square***	***p-value***	Odds Ratio
Knowledge	.899	.289	9.683	.002	2.456
Correctness	1.115	.334	11.135	.001	3.050
Off-task	-.570	.181	9.950	.002	.565
Constant	.051	.155	.106	.745	1.052

The final model for AP Science course choice in high school (Table 5) achieved a cross-validated A' of 0.822 and a cross-validated Kappa of 0.485. This model is statistically significantly better than the null model (χ^2(df = 2 N = 282) =

102.481, $p < 0.001$) and achieved a fit of R^2 (Cox and Snell) = 0.305, R^2 (Nagelkerke) = 0.407, indicating that its predictors explain 30.5-40.7% of the variance of those took AP Science in high school. The combination of middle school variables that best predicts AP Science course choice in high school consisted of correctness and boredom, where students who had more correct answers when using ASSISTments in middle school were more likely to take an AP Science course in high school, while students who were more bored were more likely to take a regular Science course in high school.

Table 5
Model Results Predicting AP Science Course Choice in High School (n = 282 students)

Features	***Coefficient***	***Standard Error***	***Chi-Square***	***p-value***	Odds Ratio
Correctness	1.114	.175	40.362	<.001	3.046
Boredom	-1.004	.222	20.390	<.001	.366
Constant	-.312	.157	3.941	.047	.732

Discussion

The findings of Study 2 showed that middle school indicators of performance and engagement are predictive of whether the student takes an AP Math class or a regular Math class, as well as whether the student takes an AP Science class or a regular Science class in high school. These findings accord with SCCT-based theoretical accounts that experiences of mastery and motivation (as early as middle school) can drive future goals, interests and choices (in high school and beyond). A student who becomes disengaged during math learning is likely to dislike math (Authors, 2008b), and in turn is less likely to take a math-related course. Eccles and Jacobs (1986) found that self-perceptions of math ability influenced math achievement and math course-taking plans, which aligns with middle school knowledge and correctness being related to the choice of AP

Math courses in high school. This finding also accords with research that finds middle school math proficiency and performance are predictive of taking more advanced math courses in high school (Finkelstein et al., 2012; Rock, Owings, & Lee, 1994). The negative relationship between off-task behavior in middle school and AP Math course choice in high school may be attributed to this disengaged behavior's negative impact on learning (Authors, 2009). For AP Science, the positive relationship between middle school correctness and choice of AP Science courses in high school aligns with middle school science performance being associated with taking advanced science courses in high school (Madigan, 1997), while middle school boredom being negatively associated with AP Science course choice in high school aligns with research on academic boredom negatively influencing academic achievement (Pekrun, et al., 2010; Tze, Daniels, & Klassen, 2016).

STUDY 3: PATH ANALYSIS FROM MIDDLE SCHOOL TO HIGH SCHOOL TO COLLEGE

Research question 3 – *What is the role that high school course choices play in the path between middle school indicators and college attendance?* – was answered by testing the pathway of the 282 students from Study 2 from the middle school (variables of knowledge, academic emotions, behavior, correctness and usage) to high school (variables AP Math and AP Science) to college (college enrollment).

Having observed variables from middle school to college, path analysis was employed in Study 3 to evaluate a pathway from middle school factors to high school variables to college outcomes, using the *Mplus* software. Around half of the student sample took AP Math (*n* = 141) and AP Science (*n* = 130) during high school, with most of them eventually enrolling in college (*n* = 225).

Methods

The model evaluated in this study (Figure 9) was designed to correspond to SCCT where learning experiences influence the development of career choices, in this case college attendance. Thus, the model developed here aimed to establish if the relationships between college attendance and middle school indicators of performance and engagement measured within computer-based learning were intermediated by high school variables of course-taking (taking regular or AP/Honors math and science courses).

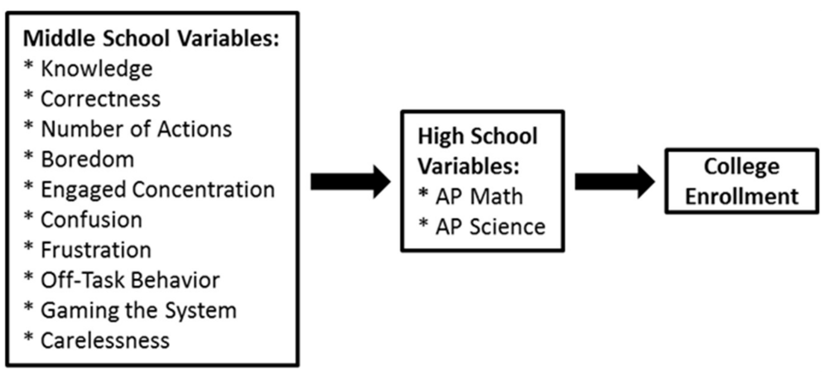

Figure 9. Model designs for Study 3's Path Analysis

Using the *Mplus* software, path analyses were conducted for 282 students who had ten middle school indicators of knowledge, academic emotions, behavior, correctness and usage, two high school variables of taking AP Math and AP Science courses, and college enrollment. A path model was initially created that consisted of the ten middle school variables, two high school variables, and the college outcome variable. However, this design did not result in a good model fit or any significant paths. Hence, we created two path models from middle school to college, using AP Math as the high school variable in one model, and

AP Science in the other. In these models, we did not consider paths straight from middle school to college (for this, see Study 1 analyses above).

Results

The path model in Figure 10 for AP Math showed good results in terms of model fit with our data of 282 students: chi-square = 5.651 df = 10, p = 0.8437, CFI =1.000 and RMSEA = 0.000 (p<.05). However, its parameter estimates showed that the significant relationship was only found between correctness and AP Math (Table 6).

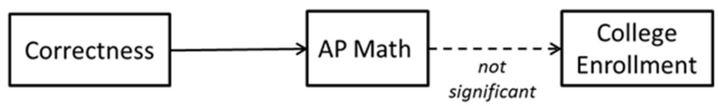

Figure 10. Path Models using AP Math as the high school variable (only significant paths shown).

Table 6
Model Results of Path Model Analysis from Middle School Knowledge, Academic Emotions, and Behavior to High School AP Math Course Choice to College Enrollment

	Estimate	*S.E.*	*p-value*	R^2
AP Math ON				0.537
Knowledge	0.192	0.519	0.711	
Carelessness	0.375	0.458	0.413	
Correctness	0.7	0.255	0.006	
Boredom	-0.042	0.177	0.812	
Number of Actions	0.136	0.146	0.352	
Engaged Concentration	-0.144	0.143	0.312	
Confusion	0.015	0.136	0.914	
Frustration	-0.001	0.155	0.997	
Off-Task	-0.246	0.155	0.112	
Gaming	0.049	0.193	0.801	
College Enrollment ON				0.028
AP Math	0.114	0.120	0.951	

Thresholds/Intercept			
College Enrollment	-0.913	0.092	<.001
AP Math	-0.03	0.093	0.747

The path model (Figure 11) for AP Science also showed good results in terms of model fit with our data of 282 students: chi-square = 6.473 df = 10, p = 0.7740, CFI =1.000 and RMSEA = 0.000 (p<.05). Similar to the regression analysis, significant relationships (Table 7) were found between correctness and AP Science (marginal, positive), boredom and AP Science (negative), confusion and AP Science (marginal, positive), and a between AP Science and college enrollment (marginal, positive).

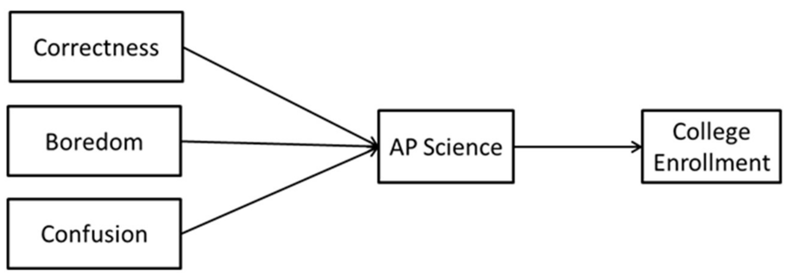

Figure 11. Path Models using AP Science as the high school variable (only significant paths shown).

Table 7
Results of Path Model Analysis from Middle School Knowledge, Academic Emotions, and Behavior to High School AP Science Course Choice to College Enrollment

1	*Estimate*	*S.E.*	*p-value*	R^2
AP Science ON				0.523
Knowledge	-0.083	0.493	0.866	
Carelessness	0.328	0.455	0.471	
Correctness	0.517	0.272	0.057	
Boredom	-0.635	0.252	0.012	
Number of Actions	-0.047	0.136	0.727	

Engaged Concentration	0.166	0.151	0.273	
Confusion	0.366	0.204	0.072	
Frustration	-0.153	0.15	0.31	
Off-Task	-0.218	0.159	0.17	
Gaming	-0.075	0.212	0.723	
College Enrollment ON				0.076
AP Science	0.195	0.1	0.051	
Thresholds/Intercept				
College Enrollment	-0.913	0.092	<.001	
AP Science	0.177	0.097	0.068	

Unlike the path model with AP Math as the high school variable, the path model with AP Science as high school variable showed a significant full path from middle school to high school to college, where affect in middle school influenced whether a student took AP Science in high school, and taking AP Science in turn influenced whether a student went to college. The models here were rather simple, but this may be an artifact of limited statistical power due to the much smaller sample size than in Study 1 above.

Discussion

Study 3 findings showed that STEM course choice in high school (i.e. taking an AP or Honors Science course) connects middle school performance and negative academic emotions (boredom, confusion) to the outcome of college enrollment. This finding suggests that cognitive and non-cognitive factors in middle school learning may influence academic choices during high school that in turn lead to college readiness. These findings accord with existing studies that show middle school performance and engagement being related to both high school course-taking and college-going outcomes. For example, Finkelstein and colleagues (2012) found that middle school math or science achievement is predictive of high school course-taking in math or science and high school achievement which influences later college-going opportunities.

CONCLUSIONS

Prior to graduating high school, students are faced with the decision of attending college. They think about what they want for a potential career, and consider which college or postsecondary institution they should attend. During K-12 learning, students are guided by their teachers or guidance counselors in discovering these options. Factors such as academic performance, engagement, self-efficacy, interests and goals are considered in this process.

As shown in this paper, students' learning experiences as early as middle school are predictive of their college attendance. Moreover, online learning environments create an opportunity to assess these learning experiences. Data from these environments can be used in evaluating students' academic and college-going pathways. One way to do this is by identifying richer measures within the students' learning experiences that current self-report measures may not capture. In assessing students' learning experiences as early as middle school—through student knowledge, academic emotions, and engaged and disengaged behavior—there is a potential for more effective interventions based on better information. These cognitive and non-cognitive factors within learning influence both students' achievement and their motivation to learn (Authors, 2013b; Fredericks, Blumenfeld, & Paris, 2004), and can manifest in the students' learning experiences –learning strategies they use in the classroom, or their behavioral and motivational engagement.

With these in mind, the models developed in this paper examined how the proposed factors of middle school student knowledge, academic emotions and behaviors of engagement or disengagement can potentially enhance theories of career development such as the SCCT model by showing how these factors are related to the eventual choice actions (Lent, Brown, & Hackett, 1994) of course-taking in high school and enrolling in college (Figure 12).

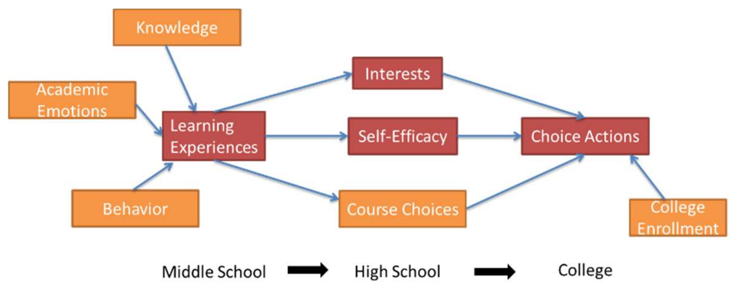

Figure 12. SCCT Model with Cognitive and Non-Cognitive Factors during Middle School Online Learning.

This paper investigated the learning mechanisms that students experience during their middle school and high school years and evaluated how they can be significant antecedents to their decisions to enroll in college, forming a model of the trajectory from students' educational experiences starting in middle school, to the student's eventual choices and outcomes related to college enrollment. This research used a variety of data sources, most prominently from an online learning environment during middle school (used in the students' curriculum). Data acquired from online learning environments allow researchers to computationally model and assess cognitive constructs such as learning, academic emotions and behavior, using current educational data mining/learning analytics methodologies. The research presented here took advantage of using educational data from online learning environments in analyzing long-term educational outcomes, one of the first studies that takes advantage of that possibility in using these data sources to conduct analysis in this area of educational research.

Beyond expanding theoretical understanding, one possible use of these findings is to give educators and career counselors new, early, nuanced information on students' career trajectories. Guidance counselors can integrate a range of types of information into their practice with students (Rottinghaus & Eshelman, 2015), providing a richer understanding than current instruments afford. Guidance counselors already have data on grades and standardized examinations, but grades and standardized exams are lagging indicators (Wentzel, 1993). By contrast, learning and performance data from systems like ASSISTments can be instantaneously available, providing timely data on how students are faring. The constructs studied here may also be amenable to gentle interventions by educators or learning software, if given relatively early in a student's academic trajectories. This research shows the significance of academic emotions and engagement in student trajectories. As such, it would be important and beneficial for these factors to be considered in instructional design.

Limitations

A limitation in this study is the lack of background variables from students (ex. gender, race, ethnicity, SES, etc) to develop a richer college attendance model that investigates whether these phenomena play out differently for students with different attributes. Also, as mentioned earlier, there may be more insights into modeling the outcomes by separating the student sample by school district, and analyzing different school districts separately. In this study, this goal was infeasible for studies 2 and 3 due to limited sample size. Hence, the college attendance models presented here represent general models across populations rather than helping us understand how these phenomena differ for different populations.

Developing proper guidance and pathways to support students in achieving academic success as they progress from middle school to high school to college necessitates a holistic and comprehensive look at the student's academic and nonacademic experiences. As such, quantitative assessments of the middle school cognitive and non-cognitive factors presented in this study should be supplemented with other measures of the student's learning experience from one grade level to another – such as SIS data (e.g. student demographics), quarterly GPA, disciplinary incidents, state test scores, or course-taking patterns – to provide additional useful insights in evaluating long-term trajectories and predictions of student outcomes (as is seen in many recent learning analytics platforms).

It is also important to note that findings in this research were studied within the context of learning activities in middle school mathematics. It is possible (though not certain) that the findings obtained here may also be true of other STEM domains, but it is an important area of future work to study how much these findings hold both in STEM and non-STEM domains such as social science and humanities. Does disengagement in a social studies class lead to a lower probability of college attendance?

As such, future work can build on the college attendance models in this study by gathering more background variables about the students, other relevant measures of achievement, self-efficacy, and interests to improve the predictive accuracy of the college attendance models; evaluating the interactions between variables; and collecting a larger sample size in order to allow for the study of how different groups differ in terms of these relationships.

The integrative research presented here is among the first studies that show the relationship of interaction-based measures of cognitive and non-cognitive constructs to long-term outcomes, tracking across several years, from middle school to college. A better understanding of how these relationships manifest over time, and the advent of reports that provide information on the variables studied here to practitioners, may help teachers and school counselors in their ongoing efforts to help students succeed in their long-term goals.

REFERENCES

Aleven, V., Mclaren, B., Roll, I., & Koedinger, K. (2006). Toward meta-cognitive tutoring: A model of help seeking with a Cognitive Tutor. *International Journal of Artificial Intelligence in Education*, *16*(2), 101-128.

Arroyo,I., Ferguson,K., Johns,J., Dragon,T., Meheranian,H., Fisher,D., Barto,A., Mahadevan,S., Woolf,B.P. (2007) Repairing Disengagement with Non-Invasive Interventions. In *Proceedings of AIED 2007* (pp. 195-202).

Arnold, K. E., & Pistilli, M. D. (2012, April). Course signals at Purdue: Using learning analytics to increase student success. In *Proceedings of the 2nd international conference on learning analytics and knowledge* (pp. 267-270). ACM.

Authors.(2004). Citations blinded for review.

Authors.(2006).

Authors.(2008a).

Authors.(2008b).

Authors.(2009).

Authors.(2010a).

Authors.(2010b).

Authors.(2011).

Authors.(2013a).

Authors.(2013b).

Authors.(2013c).

Authors.(2014a).

Authors.(2014b).

Authors.(2015a).

Authors.(2015b).

Balfanz,R. (2009). Putting middle grades students on the graduation path: A policy and practice brief. *Everyone Graduates Center & Talent Development Middle Grades Program*.

Bandura,A. (1986). *Social foundations of thought and action* (pp. 5-107). Prentice Hall: Englewood Cliffs, NJ.

Bowers,A.J. (2010). Grades and graduation: A longitudinal risk perspective to identify student dropouts. *The Journal of Educational Research*, 103(3), 191-207.

Cabrera,A.F. (1994). Logistic regression analysis in higher education: An applied perspective. *Higher education: Handbook of theory and research*, *10*, 225-256.

Cabrera,A.F., & La Nasa,S.M. (2000). Understanding the college-choice process. *New directions for institutional research, 2000* (107), 5-22.

Cabrera,A.F., La Nasa,S.M. and Burkum,K.R. (2001). *Pathways to a Four-Year Degree: The Higher Education Story of One Generation*. Center for the Study of Higher Education.

Camblin,S. (2003). *The middle grades: Putting all students on track for college*. Honolulu, HI: Pacific Resources for Education and Learning.

Canfield,W. (2001). ALEKS: A Web-based intelligent tutoring system. *Mathematics and Computer Education*, 35(2), 152-158.

Carnevale,A.P., & Rose,S.J. (2003). *Socioeconomic status, race/ethnicity, and selective college admissions*. New York: Century Foundation.

Clarke-Midura,J., & Dede,C. (2010). Assessment, technology, and change. *Journal of Research on Technology in Education*, 42(3), 309-328.

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

Cohen,J. (1960). A coefficient of agreement for nominal scale. *Educ Psychol Meas*, *20*, 37-46.

Conley,D.T. (2007). *Redefining College Readiness*. Educational Policy Improvement Center.

Conley, D. T. (2008). *College knowledge: What it really takes for students to succeed and what we can do to get them ready*. John Wiley & Sons.

Conley, D., Lombardi, A., Seburn, M., & McGaughy, C. (2009). *Formative Assessment for College Readiness: Measuring Skill and Growth in Five Key Cognitive Strategies Associated with Postsecondary Success.* Online Submission.

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.

Craig,S., Graesser,A., Sullins,J., & Gholson,B. (2004). Affect and learning: an exploratory look into the role of affect in learning with AutoTutor. *Journal of Educational Media*, 29(3), 241-250.

Csikszentmihalyi,M. (1990) *Flow: The Psychology of Optimal Experience*. Harper-Row, New York.

D’Mello,S.K., Craig,S.D., Witherspoon,A., Mcdaniel,B., & Graesser,A. (2008). Automatic detection of learner’s affect from conversational cues. *User modeling and user-adapted interaction*, 18(1-2), 45-80.

D'Mello,S.K., Lehman,B. Pekrun,R., & Graesser,A.C. (2014). Confusion Can be Beneficial For Learning. *Learning & Instruction*, 29(1), 153-170.

Drummond,J., & Litman,D. (2010). In the zone: Towards detecting student zoning out using supervised machine learning. In *Intelligent Tutoring Systems* (pp. 306-308).

Eccles,J.S., & Jacobs,J.E. (1986). Social forces shape math attitudes and performance. *Signs*, *11*(2), 367-380.

Eccles,J.S., Vida,M.N., & Barber B. (2004). The relation of early adolescents’ college plans and both academic ability and task-value beliefs to subsequent college enrollment. *The Journal of Early Adolescence*, 24(1), 63-77.

Fancsali, S. (2014, July). Causal discovery with models: behavior, affect, and learning in cognitive tutor algebra. In *Educational Data Mining 2014*.

Farrington,C.A., Roderick,M., Allensworth,E., Nagaoka,J., Keyes,T.S., Johnson,D.W., & Beechum,N.O. (2012). *Teaching Adolescents to Become Learners: The Role of Noncognitive Factors in Shaping School Performance--A Critical Literature Review.* Consortium on Chicago School Research.

Feng,S., D’Mello,S., & Graesser,A.C. (2013). Mind wandering while reading easy and difficult texts. *Psychonomic bulletin & review*, 20(3), 586-592.

Feng, M., Heffernan, N., & Koedinger, K. (2009). Addressing the assessment challenge with an online system that tutors as it assesses. *User Modeling and User-Adapted Interaction*, *19*(3), 243-266.

Finkelstein, N., Fong, A., Tiffany-Morales, J., Shields, P., & Huang, M. (2012). College Bound in Middle School & High School? How Math Course Sequences Matter. *Center for the Future of Teaching and Learning at WestEd*.

Fredricks,J.A., Blumenfeld,P.C., & Paris,A.H. (2004). School engagement: Potential of the concept, state of the evidence. *Review of educational research*,74(1), 59-109.

Griffith,A.L., & Rothstein,D.S. (2009). Can't get there from here: The decision to apply to a selective college. *Economics of Education Review*, 28(5), 620-628.

Hanley,J., & McNeil,B. (1982). The Meaning and Use of the Area under a Receiver Operating Characteristic (ROC) Curve. *Radiology* 143, 29-36.

Hawn, A. (2015, March). The bridge report: bringing learning analytics to low-income, urban schools. In *Proceedings of the Fifth International Conference on Learning Analytics And Knowledge* (pp. 410-411). ACM.

Hosmer Jr,D.W., Lemeshow,S., & Sturdivant,R.X. (2013). *Applied logistic regression* (Vol. 398). John Wiley & Sons.

Hossler,D., Braxton,J., & Coopersmith,G. (1989). Understanding student college choice. *Higher education: Handbook of theory and research*, 5, 231-288.

Karweit,N., & Slavin,R.E. (1982). Time-on-Task - Issues of Timing, Sampling, and Definition. *Journal of Educational Psychology*, 74(6), 844-851.

Kellam,S.G., Ling,X., Merisca,R., Brown,C.H., & Ialongo,N. (1998). The effect of the level of aggression in the first grade classroom on the course and malleability of aggressive behavior into middle school. *Development and Psychopathology*, 10, 165–185.

Khajah, M., Lindsey, R. V., & Mozer, M. C. (2016). How deep is knowledge tracing? In T. Barnes, M. Chi, & M. Feng (Eds.), *Proceedings of the Ninth International Conference on Educational Data Mining* (pp. 94-101). Educational Data Mining Society Press.

Koedinger,K.R., & Corbett,A.T. (2006). Cognitive tutors: Technology bringing learning science to the classroom. In K. Sawyer (Ed.), *The Cambridge Handbook of the Learning Sciences*. Cambridge University Press.

Kort,B., Reilly,R., Picard,R. (2001). An Affective Model Of Interplay Between Emotions And Learning: Reengineering Educational Pedagogy—Building A Learning Companion. In *Proceedings IEEE ICALT 2001*, 43-48.

Lehman, B., D'Mello, S., & Graesser, A. (2012). Interventions to regulate confusion during learning. In *Intelligent Tutoring Systems* (pp. 576-578). Springer Berlin/Heidelberg.

Lent,R.W., Brown,S.D., & Hackett,G. (1994). Toward a unifying social cognitive theory of career and academic interest, choice and performance. *Journal of Vocational Behavior*, 45(1), 79–122.

Lent, R. W., Brown, S. D., & Hackett, G. (2000). Contextual supports and barriers to career choice: A social cognitive analysis. *Journal of Counseling Psychology*, 47(1), 36–49.

Madigan, T. (1997). Science Proficiency and Course Taking in High School: The Relationship of Science Course-Taking Patterns to Increases in Science Proficiency between 8th and 12th Grades.

McQuiggan, S. W., Mott, B. W., & Lester, J. C. (2008). Modeling self-efficacy in intelligent tutoring systems: An inductive approach. *User modeling and user-adapted interaction*, 18(1-2), 81-123.

Milliron, M. D., Malcolm, L., & Kil, D. (2014). Insight and action analytics: Three case studies to consider. *Research & Practice in Assessment*, *9*.

Núñez,A.M., & Bowers,A.J. (2011). Exploring what leads high school students to enroll in hispanic-serving institutions a multilevel analysis. *American Educational Research Journal*, *48*(6), 1286-1313.

Pekrun,R., Goetz,T., Daniels,L.M., Stupnisky,R.H., & Perry,R.P. (2010). Boredom in achievement settings: Exploring control–value antecedents and performance outcomes of a neglected emotion. *Journal of Educational Psychology*, 102(3), 531.

Pekrun,R., & Linnenbrink-Garcia,L. (2012). Academic emotions and student engagement. In *Handbook of research on student engagement* (pp. 259-282).

Razzaq,L., Feng,M., Nuzzo-Jones,G.,... & Rasmussen,K.P. (2005). The Assistment project: Blending assessment and assisting. In *Proceedings of AIED 2015* (pp. 555-562).

Reinke,W.M., & Herman,K.C. (2002). Creating school environments that deter antisocial behaviours in youth. *Psychology in the Schools*, 39, 549–559.

Rock, D. A., Owings, J. A., & Lee, R. (1994). *Changes in math proficiency between 8th and 10th grades*. US Department of Education, Office of Educational Research and Improvement, National Center for Education Statistics.

Roderick,M., Coca,V., & Nagaoka,J. (2011). Potholes on the road to college high school effects in shaping urban students' participation in college application, four-year college enrollment, and college match. *Sociology of Education*, 84(3), 178-211.

Roderick,M., Nagaoka,J., & Coca,V. (2009). College readiness for all: The challenge for urban high schools. *The Future of Children*, 19(1), 185-210.

Rottinghaus,P.J., & Eshelman,A.J. (2015). Integrative approaches to career intervention. In *APA handbook of career intervention, Vol 2: Applications.* 25-39.

Rowe,J.P., McQuiggan,S.W., Robison,J.L., & Lester,J.C. (2009). Off-Task Behavior in Narrative-Centered Learning Environments. In *AIED 2009* (pp. 99-106).

Rozin,P., & Cohen,A.B. (2003). High frequency of facial expressions corresponding to confusion, concentration, and worry in an analysis of naturally occurring facial expressions of Americans. *Emotion*, 3(1), 68.

Sabourin, J., Rowe, J., Mott, B., Lester, J. (2011). When off-task is on-task: The affective role of off-task behavior in narrative-centered learning environments. In Proceedings of *Artificial Intelligence in Education 2011*, 534-536.

Tze, V. M., Daniels, L. M., & Klassen, R. M. (2016). Evaluating the relationship between boredom and academic outcomes: a meta-analysis. *Educational Psychology Review*, *28*(1), 119-144.

Vaessen, B. E., Prins, F. J., & Jeuring, J. (2014). University students' achievement goals and help-seeking strategies in an intelligent tutoring system. *Computers & Education*, *72*, 196-208

Wentzel,K.R. (1993) Does being good make the grade? Social behavior and academic competence in middle school. *Journal of Educational Psychology*, 85 (2), 357-364.

Witten,I.H., & Frank,E. (2005). *Data Mining: Practical machine learning tools and techniques*. Morgan Kaufmann.