

Identifying Relevant User Behavior, Predicting Learning, and Persistence in an ITS-based After-school Program

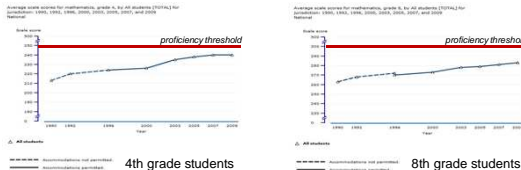


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Project Summary

- Mathematics is an essential 21st century skill.
- Many countries are failing to reach proficient levels in Mathematics
- National Center for Education Statistics (2008, 2010)



Learning Outside of School

- After-school programs are an untapped resource (Gayl, 2004; Kugler, 2001; Miller, 2003)
 - only 11% of students participate in after-school programs
 - most programs are skill based and do not target academic topics
- After-school programs can improve mathematics performance
 - 6th and 7th grade students that regularly attend after-school programs score about 12 percentile points higher in mathematics than their peers (Vandell, 2007).
 - after-school programs that implement valid tutoring techniques display the greatest gains (Lauer, 2003).
- After-school programs encounter several challenges (Vandell et al., 2005)
 - student attendance is sporadic
 - an academic focus can feel like additional school or classroom time

Our After-school Math Program

- Occurred within the Jackson-Madison County School System (J-MCSS)
- Targeted 6th grade students at 5 middle schools
- Duration of 21 weeks (two days per week, two hours per day)
- Conducted by 16 certified math teachers
- Point-based retention program
 - student received points for attendance
 - spend points for gifts at the end of the program

Daily Schedule

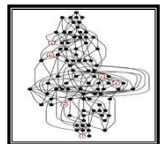
Training 20 min.

Break 20 min.

Training 20 min.

Break 20 min.

Training 20 min.



Example Knowledge Space

- Used the **ALEKS (Assessment and Learning in Knowledge Spaces)** web-based learning system
- AI-based Knowledge Space Theory (KST)
 - Representation of a large number of possible knowledge states within a topic (e.g. Mathematics)
 - Models learners' current knowledge: including what the student knows, does not know, and is ready to learn

Supporting evidence for ALEKS software

- ALEKS in middle school classrooms** (Sullins et al., 2013)
 - 6th grade math classrooms
 - positive correlations between state test scores and ALEKS topics learned
- ALEKS in college classrooms** (Hu et al., 2013)
 - college statistics courses
 - ethnicity performance gap disappeared for ALEKS classes
 - gap persisted in traditional classrooms
- ALEKS in an after-school program** (Craig et al., 2013; Hu et al., 2012)
 - 6th grade mathematics
 - ALEKS-led classes performed at the same level as teacher-led classes
 - program students outperformed non-program students in math
 - required less assistance from teachers during the program
 - time working in ALEKS was positively correlated with performance
 - $r(126) = .474, p < .001$ (Craig et al. 2011).

Three Investigations of How Student Behaviors within ALEKS Impact Learning in an After-school Setting

Predicting Learning within ALEKS

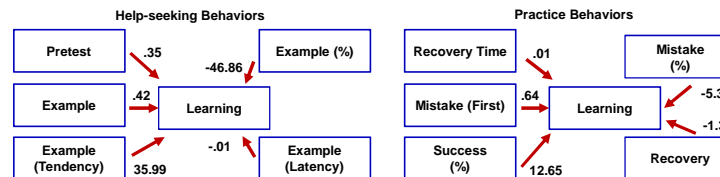
Method

- 204 sixth grade students in Years 2 and 3 of the program
- Analyses related to behavior and learning
 - Analysis 1: help-seeking
 - Analysis 2: practice
- Logistic mixed effect models
 - used 10-fold cross validation
 - Help-seeking: M2e = .81
 - Practice: M2e = .75



Learning Behaviors within ALEKS

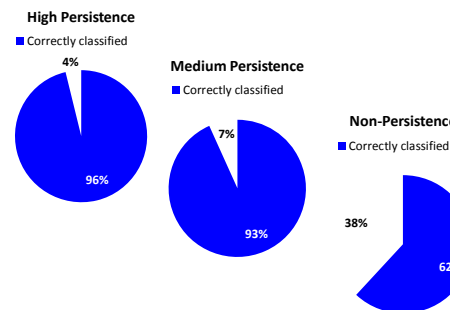
- Example:** read the explanation before attempting a topic
- Example (Proportion):** proportion of explanations being read (the number of explanations/ the number of learning behaviors)
- Example after Mistake:** read the explanation immediately after making the mistake
- Example (Latency):** delay to seek explanations after making mistakes
- Example (Tendency):** tendency to seek explanations to avoid making mistakes (the number of explanations/ the number of mistakes and explanations)
- Mistake (First):** make a mistake in the first question of the topic
- Mistakes (Proportion):** proportion of mistakes (the number of mistakes/ the number of learning behaviors)
- Success (Proportion):** proportion of successes (the number of successes/ the number of learning behaviors)
- Recovery:** proportion of successes after mistakes (the number of successes after mistakes/ the number of activities after mistakes)
- Recovery Time:** time used to correct errors without reading explanations



Predicting Student Persistence within ALEKS

Method

- 114 6th grade students from Years 2 and 3
 - included 92,235 log files
- Predicting student persistence
 - "high persistence" (trials > 15)
 - "medium persistence" (10 ≤ trials ≤ 15)
 - "non-persistence" (trials < 5, no mastery)
- Logistic regression predictors
 - prior knowledge
 - topic difficulty
 - time period in the program
- Results**
 - High persistence: $R^2 = .03$; correctly classified 96.2% of cases
 - Medium persistence: $R^2 = .02$; correctly classified 93.3% of cases
 - Non-persistence (without mastery): $R^2 = .07$; correctly classified 62.5% of cases



Learning Strategies within ALEKS

Method

- 372 6th grade students from Years 2 and 3
- Included 55,281 learning sequences:
- Typical activities: *correct, wrong, explain, mastery, failed, left the attempt*
- Identified **10 strategy clusters (C)**

Identifying Learning Strategies

- Sequencing:** Discrete Markov Models
- Clustering:** k-means algorithm

- C1:** three correct practices in a row, with mastery (9% of attempts)
- C2:** quick mastery (11%)
- C3:** continue practicing after mastery (6%)
- C4:** frequently request worked examples; only attempt when confident (7%)
- C5:** request worked examples after mistake; attain correct answer and mastery (12%)
- C6:** request worked examples then quit without practice (13%)
- C7:** request worked examples after error, continue to give incorrect response, then quit (17%)
- C8:** correct at 1st practice but wrong at 2nd & 3rd; request worked examples but only get half of practices correct (6%)
- C9:** all practices are wrong; request worked example after two errors; continue with errors; quit/failure (9%)
- C10:** all practices are wrong; reach failure twice (9%)

Conclusions

Three Major Findings

- clustered learner strategies and demonstrated that context is important
- predicted learning based on behavior within ALEKS (help-seeking and practice)
- successfully predicted student persistence on ALEKS problems

Overall, the after-school program with ALEKS was highly successful

- improved students math ability (Hu et al., 2011)
- students continued to perform at the same levels of impact over 4 years
- evidence for decreasing achievement gaps typically found with minority populations (Huang et al., 2016)
- ITS after-school program could be an effective alternative for school systems that have limited trained teachers
- still need to better understand the process of learning with this technology

Project Information

Cheney K. R., Craig, S. D., Anderson, C., Bargagliotti, A., Graesser, A. C., Sternbisky, A., Okumabua, T. & Hu, X. (2011). Closing the knowledge gap in mathematics among sixth grade students using ALEKS. In M. Koehler & P. Mishra (Eds.), Proceedings of the 19th International Conference for the Society for Information Technology & Teacher Education (pp. 1425-1427). Chesapeake, VA: AACE.

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