Causal Modeling of user data from a math learning environment with game-like elements

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Abstract. We have created a math learning environment with game-like elements such as narrative, visual feedback, personalization, collection, etc. We made a study with four different versions of the tutor with different degree of 'game-like' and found that students preferred more 'game-like' tutor but we were not able to detect any conclusive difference in learning. Based on the data we collected through survey, logs and tests, we also built a causal model to understand the interrelationships between different student and tutor variables.

1 Introduction

Although educational games intend to make learning more enjoyable, they may add additional cognitive load among learners and have been empirically shown to generally be less effective than intelligent tutors in terms of learning gains [1]. Hence, instead of completely integrating educational content into a game framework, we choose to build a tutor integrating game-like elements, elements of games that are responsible for their engaging nature. We have developed *Monkey's Revenge*, a coordinate geometry tutor, which consists of a sequence of coordinate geometry problems wrapped in a visual cover story. We integrated game-like elements such as narrative, immediate visual feedback, personalization, and collection. Students can request hints and get bug messages as they stumble on misconceptions. Our aim is to iteratively assess each game-like element in terms of its engaging nature and impact on learning so that we can find an optimal balance of engagement and learning. To make comparative analysis of the game-like elements, we created four different versions of *Monkey's Revenge* with different degree of "game-like" (Table 1). A total of 297 middle school (12-14 year olds) students from four Northeastern schools in the United States participated in this study. The students were randomly assigned to the experimental conditions and we collected their survey data along with tutor logs. The students also did an 8-item pre- and post-test. We found that students who had a more "game-like" tutor reported liking the tutor more, but we found no conclusive difference in learning gain. But beyond confirming the main effect of the intervention, we are also interested in making exploratory analysis of the user data and have used causal modeling [2] approach using a software, TETRAD [3]. A causal model makes the additional assumption that the links between nodes represent causal influence.

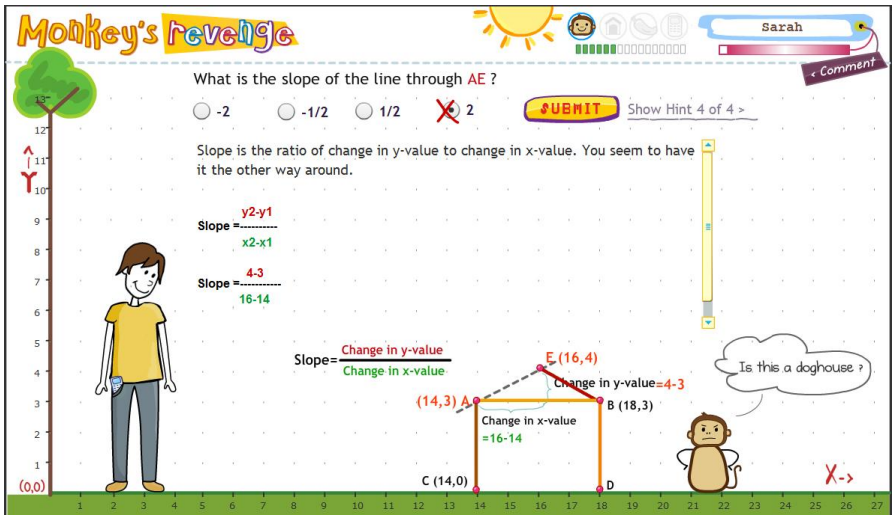

Figure 1 Screenshot of *Monkey's Revenge*

Table 1 Students' data across experimental conditions (means and 95% CI))

Tutor	Like tutor (max 5)	Learning gain (max 10)
Monkey's Revenge	3.9+/-0.3	0.41+/-0.6
Monkey's Revenge without visual feedback	3.8+/-0.3	0.88+/-0.6
Monkey's Revenge without narrative	3.6+/-0.3	0.31+/-0.6
Basic tutor with hints and bug message	2.8+/-0.3	0.45+/-0.6

We used factor analysis to reduce 16 survey questions into six variables. We also specified the causal hierarchy among the variables in the form of knowledge tiers [3] as specified in Table 2; variables in a lower tier cannot affect variables in higher tiers.

Table 2 Student and tutor variables in causal model

Gender –tier 1	
Students' attitude and preference (survey)-tier 2	***likeMath*** (math is interesting); ***mathSelfConcept*** (I am afraid of Math.; I am afraid of doing word problems.); ***pedagogicalpreference*** **(**I like learning from computers, I like real world examples)
Prior knowledge –tier 3	***preTestScore*** (students' score on pre test)
Tutor activities (tutor logs) –tier 4	***%correct*** (ratio of correct problems); ***avgAttemptTime*** (average time student spent on each attempt); ***avgHints*** (average number of hints students asked on each question)
Opinion on tutor (survey)-tier 4	***tutorHelpful; tutorConfusing; likeTutor*** (This tutor looks interesting. I liked this tutor. I will recommend to a friend. This is better than other computer math programs I have)
Learning (test) –tier 5	***prePostGain*** (students' gain score from pre to post test score)

2 Interpretation of model: causal claims and causal inference

We made a randomized controlled trial on the tutor's degree of "game-like". Other than this variable, the inferences we are making from our causal models are solely based on statistical independencies within data, domain knowledge we added, and causal assumptions of TETRAD's inference algorithm. We are interested to see how different student subpopulations receive the tutor intervention and how their characteristics are related to their tutor activities and overall performance and gain.

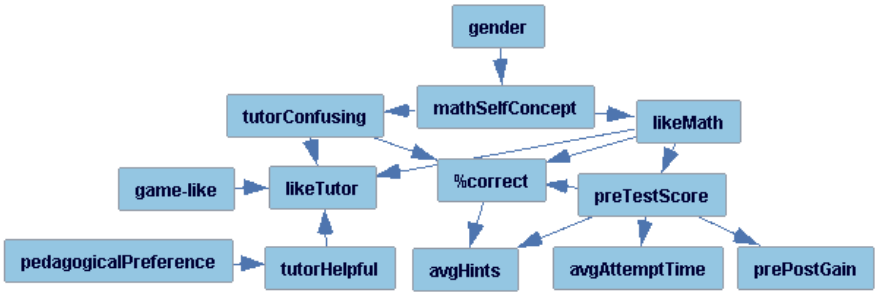

Figure 2 Causal model created using TETRAD ($p<0.05$)

Gender: Female students have poorer self concept in math which makes math less enjoyable to them.

Math attitude: Students who like math have higher prior knowledge (*preTestScore*) and higher performance (*%correct*). Students who have poor self concept in math found the tutor confusing and that also influenced their performance

Pedagogical preference: Students who had preference for computer and real world examples found the tutor helpful which made them like the tutor more.

Engagement, performance and learning: We did not find any support for student engagement leading to better learning (*prePostGain*). However, we found that the students who like math have better performance (*%correct*) irrespective of their pre test (direct link *likeMath→%correct*). While it is possible that pre test did not capture all variance in prior knowledge, an alternative hypothesis for this indirect effect is that is that the students who like math are more engaged and perform better.

Since the causal model is limited to observed variables and causality is underdetermined by correlation, we cannot necessarily make causal claims based solely on the model. However, the causal inferences made by the model have generated some interesting hypotheses that we would like to further investigate.

References

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