Achievement versus Experience: Predicting Students' Choices during Gameplay

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ABSTRACT
This study investigates how we can effectively predict what type of game a user will choose within the game-based environment iSTART-2. Seventy-seven college students interacted freely with the system for approximately 2 hours. Two models (a baseline and a full model) are compared that include as features the type of games played, previous game achievements (i.e., trophies won, points earned), and actions (i.e., iBucks/points spent, time spent on games, total games played). Using decision tree analyses, the resulting best-performing model indicates that students' choices within game-based environments are not solely driven by their recent achievement. Instead a more holistic view is needed to predict students' choices in complex systems.

Keywords
Game-based environments, Modeling, Decision tree analysis

1. INTRODUCTION
Game-based environments often afford fine-grained examinations of patterns in students' behaviors during gameplay and how they are related to cognitive skills and learning outcomes [1,2]. However, such previous work has not examined the driving force behind *why* a student chooses a specific activity or interaction within a game environment. In the current work, we compare two models. The first model is a parsimonious "1-back" model that assumes that students' choices are directly related to (and predicted by) their most recent game choice within the system and their achievements (in terms of the type of trophy won). Thus, if a student is performing well in one activity, they will continue to play that activity (or one similar to it) – *achievement behavior* [3]. The second, full model assumes that students' choices (of game type in this case) are related more comprehensively to a holistic combination of their previous *experiences* within the environment, including the types of games played, game achievements, and actions. This model follows the assumption that students' choices are influenced by a range of factors that is broader than their most recent choice and achievements. This paper is an exploratory study that attempts to answer: *what impacts students' choices within game-based environments?*

1.1 iSTART-2
Our analysis is conducted within the context of the Interactive Strategy Training for Active Reading and Thinking-2 (iSTART-2) system, designed to provide students with self-explanation strategy instruction to improve reading comprehension [1, 4]. After viewing five instructional videos, each covering a reading strategy, students are transitioned to a practice interface in which they can engage with a suite of educational games. Games involve either *generative* or *identification* practice. Generative practice games require students to type their own self-explanations while reading a text. Identification mini-games require students to read self-explanations that are ostensibly written by other students, and select which of the five strategies was used to generate each self-explanation. Students receive feedback about whether their choice was correct or incorrect.

iSTART-2 offers an ideal environment to explore questions about choice within open learning environments because students are free to choose which practice games to play. During each of the practice games, students earn points for writing high quality self-explanations or selecting the correct strategies. Based on students' score at the end of each game, theycan earn trophies (gold, silver, bronze), *iSTART Points,* and *iBucks*. iSTART Points determine students' current level within the system. iBucks are the system currency and can be spent to customize players' avatars, change background colors, or buy access to the identification games. In the current study, they were provided with an abundance of iBucks to allow them to freely interact with all features.

2. METHODS
2.1 Participants and Procedure
The study included 77 students (18-24 years) from a large University in the Southwest US. We conducted a 3-hour session consisting of a pretest, strategy training (via iSTART-2), extended game-based practice within iSTART-2, and a posttest. For our analyses here, we solely examined data from the time students spent in the game-based practice menu of iSTART. Each student spent approximately 2 hours interacting freely within the game-based interface, with his or her actions logged into the iSTART-2 database.

2.2 Development of Machine-Learned Models of Game Choice
To develop models that predict next game choice from previous achievement in an iSTART-2 game, we distilled features from the interaction logs of the 77 students who interacted with iSTART-2. A total of 1,562 action records were created for these 77 students, where each action record had 13 distilled features. Each record was labeled with the current game choice (at time *n*; 1 = identification game, 0 = generative game), having features corresponding to information about previous gameplay actions (at time *n-1*) in either an identification game or a generative game. In developing the two models to predict students' game choice, we employed student-level cross-validation for a decision tree classifier that uses the J48 implementation [5] that builds a

decision tree from a set of labeled training data. The baseline 1-back model included 2 features: previous type of game played, and type of trophy earned on the previous game. The full model included 11 additional features. The features that involved prior gameplay achievements and actions included: the number of iBucks won/spent, the number of iBuck bonus points won/spent, and the number of iSTART points won/spent the previous time the student played that game type. The remaining five features were aggregates of a student's achievements and actions so far: number of trophies achieved, number of generative games played, number of identification games played, average time played in a generative game, and average time played in an identification game.

3. RESULTS

For the 1-back model that predicts game choice based solely on previous game choice and achievement, students in our data set played a total of 1,562 games in iSTART – 1,144 instances of an identification game played and 418 instances of a generative game. The baseline model performed poorly under student-level cross-validation (see Table 1). This results in an imbalance, with precision of 38.46% and recall of 4.78%. The cross-validated A' is 0.603 (correctly predicted a game choice to be an identification game 60.3% of the time) and cross-validated Cohen's Kappa is 0.208 (model's accuracy was only 2.8% better than chance). This baseline model mainly predicts that students who have just played an identification game will select another identification game, regardless of their trophy achievement. It also predicts that many students who have just played a generative game, but did not receive any trophy, will select an identification game next.

Table 1. Cross-validated confusion matrix of baseline model

	Identification Game (True)	Generative Game (True)
Identification Game (Predicted)	1112	398
Generative Game (Predicted)	32	20

The second model resulted in the best-performing J48 tree with six features: (1) type of trophy from previous game played, (2) number of identification games played so far, (3) number of generative games played so far, (4) iSTART bonus iBucks spent in previous interaction, (5) iSTART points won in previous game, and (6) iSTART iBucks spent in previous interaction.

Table 2. Cross-validated confusion matrix of comprehensive model

	Identification Game (True)	Generative Game (True)
Identification Game (Predicted)	1069	125
Generative Game (Predicted)	75	293

This second model performed significantly better under cross-validation, classifying 1194 game choices as identification games, and 368 game choices as generative games (see Table 2), with a precision of 80.45% and recall of 70.10%. Our cross-validated A' and Cohen's Kappa also increased considerably, to A' = 0.907 and Cohen's Kappa = 0.660. Our second model yields a decision tree size of 61, with 34 decision rules (paths from root to leaf). Some examples of rules within this model include:

1) IF a student has at least played one generative game so far, AND spent more than 50 iSTART iBucks, THEN the next game the student will play is an IDENTIFICATION GAME (Confidence: 99.5%).
2) IF in a previous game the student won more than 610 iSTART points in a previous game, but spent 861 or fewer iSTART iBucks in a previous game, THEN the next game the student will play is an IDENTIFICATION GAME (Confidence: 97.0%).
3) IF a student has not played any generative game so far, AND spent no iSTART iBucks in a previous game, AND has received a BRONZE trophy in the previous game played, THEN the next game the student will play is an GENERATIVE GAME (Confidence: 83.33%).
4) IF a student has not played any generative game so far, AND spent no iSTART iBucks in a previous game, AND has received a SILVER trophy in the previous game played, THEN the next game the student will play is an GENERATIVE GAME (Confidence: 100%).

4. DISCUSSION

Results from this exploratory analysis suggest that students' choices in activities do not rely solely on previous game trophy achievement or previous game choice (first baseline model), but instead students' choices seem to be guided by their overall experience and interactions within the system (second comprehensive model). While this finding is not entirely surprising, it does help researchers shed light upon which features in a game-based environment are impacting students' choices. Indeed, there are many factors that impact students' choices within game-based environments. Thus, within environments where students are afforded a high amount of agency, user models will benefit by incorporating a more complete set of interaction features as a means to represent students' game experience more completely. In the future, we will employ Markov analyses in combination with decision tree analysis in an effort to gain a deeper understanding of what drives students' choices within a game-based environment. Although interactions within agency-driven environments are highly complex, this project demonstrates that they are predictable using machine learning algorithms.

5. ACKNOWLEDGMENTS

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6. REFERENCES

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